Modeling Overlapping Execution/Observation Brain Pathways

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***Abstract*— Recent brain imaging studies on primates revealed that a network of brain areas is activated both during observation and during execution of movements. The present work aims at modeling this group of areas, implementing a distributed computational system. The modeling process follows the agent-based coevolutionary framework that is very effective in terms of designing complex distributed systems addressing successfully the multi-modality of the interacting regions. The implemented model is successfully embedded in a simulated humanoid robot, replicating existing biological findings.**

I. Introduction

Observing the actions of other subjects and assigning meaning to them is a fundamental aspect of social communication and constitutes an efficient behavior of mammals. Recent brain imaging studies investigate where and how observed actions are represented in the primate cortex, providing evidence for the existence of an action observation – execution overlapping system. The well known mirror-neurons firing both when a monkey grasps 3-D objects and when it observes humans executing the same movements was a major contribution to this direction [23]. Additional studies [10],[16] indicate the existence of a much wider network of brain areas being activated both during observation and execution. Thus, it is of major interest to model computationally this overlap, investigating which are the benefits to the brain functionality from following this architecture, and additionally what is the role that partial structures play in the composite network.

The present work aims at modeling the overlapping observation-execution network of brain areas, as a means to explore how the interactions of specialized components give rise to integrated brain functions. Specifically, we study brain functionality when the subject either executes or observes arm reaching towards objects, in the 3D space.

The model is implemented by following the recently introduced agent-based coevolutionary framework, that has been shown to facilitate the design of complex, distributed, brain-like systems [13],[14],[15]. Following this approach, we are capable of systematically considering biological findings showing that similar primary motor and somatosensory patterns of activity are deployed during the observation and execution of the same movement. Moreover, in order to prove the validity of results, the implemented model is embedded in a simulated humanoid robot that facilitates environmental interaction.

The rest of the paper is structured as follows. In section II we describe the architecture of the model, discussing the network of brain areas necessary for execution and observation to take place. The next section reviews previous modeling efforts in the area. In section IV we outline the agent-based coevolutionary framework that was adopted for deriving the computational model. Experimental results discussing the design of the model are presented in the next section. Finally, section VI highlights conclusions and directions for future work.

II. Model Architecture

Given the connectivity of the brain [20], we have implemented a graph of the regions involved in observation and execution of movements (Fig. 1). In general, these areas integrate information from a variety of sources. The present study investigates the complications of object reaching, focusing only on visual and proprioceptive information. Particularly, inferior parietal lobule IPL accepts visual information regarding the location of the object in the 3D space, while superior parietal lobule SPL receives proprioceptive information from primary sensory cortex (S1). Both of them are connected to Premotor cortex (PM) transferring object related features that will drive goal-directed movement. Premotor cortex having a crucial role in the functionality of the whole network accepts also input from Temporal cortex (TmpC) that processes motion characteristics of the visually moving arm (for both the case of observation and execution). Additionally PM accepts input from a higher level component representing Prefrontal cortex (PFC) that specifies whether the model will operate in an execution or observation mode. This decision is based on preprocessed visual information addressing the identity of the moving hand. Relating this assumption to monkey experiments, we hypothesize that animals can easily distinguish their-own arm from the arm of the human demonstrator, based on descriptive object properties, including color and size. We need to note that resolving the mode of operation in an intrinsic way is essential for bootstrapping the operation of the model. This is because the very same model has to operate either in an execution or in an observation mode. In the former case, the output

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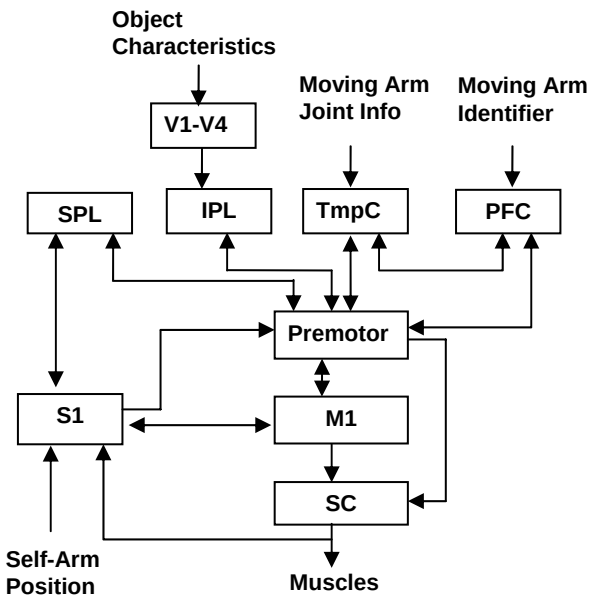


Fig. 1. Graphical interpretation of the model

from PM is incorporated to the Primary Motor cortex (M1) being responsible for decoding plans to detailed motion orders, while Spinal Cord (SC) distributes these orders to the muscles. In the latter case, the motion identified in PM is monitored by M1 and S1 for further matching and confirmation.

As already mentioned, recent studies [10] indicate that besides the overlapping activations in the premotor cortex, there exists a wider group of co-activation overlaps during execution and observation. This path extends from the premotor cortex, to the primary motor (M1) and somatosensory (S1) areas. In addition the same study indicates that the activation levels in both the primary and somatosensory cortexes fluctuate at approximately 50%, compared to the ones during execution. Such results are very important in shading light in the brain functionalities underlying execution and observation, by indicating the existence of an elaborate mental simulation mechanism. Our work aims at modeling and investigating the brain areas and relevant mechanisms that are exactly involved in execution/observation actions

III. Previous Work

Contemporary models addressing overlapping brain functionality during execution and observation, focus on the implications of the 'Mirror neurons' concept. Among the most prominent models is the Mirror Neuron System (MNS) [2] that models the interactions among the primary (M1), pre-motor (PM) and Anterior Intraparietal (AIP) areas to provide a framework for replicating grasp related behaviors. The architecture extends the functionality of the Fagg-Arbib-Rizzolatti-Sakata (FARS) model [3] that focuses on the circuitry of the AIP and F5 regions, to include grasp related actions. At its core, the MNS model uses the Dynamic Recurrent Associative Memory Architecture (DRAMA) [4], a modified Kohonen network which has been demonstrated to be resilient in learning the spatio-temporal invariance of behaviors [5]. Variations of associative memory architectures employing Hebbian rules have been used in different settings and experiments, including the "non-monotonic neural net" [6] which has been used to incorporate vision and motor control in imitation tasks [7], or the "Higher Order Hopfield Net" [8] that was employed to deal with the high correlated patterns of streamed vision input [9].

However the fusion between sensory input and motor output assumed in these models is only partial as the units responsible for recognizing the actions of another agent are decoupled from the action generating circuitry of the model (e.g. [2]). Furthermore, these models do not investigate the common activation patterns during observation and execution in brain areas different than premotor cortex (particularly F5). The model presented in the current work addresses both issues raised above.

IV. The Agent-Based CoEvolutionary Framework

A main problem with modeling the brain is confronting the multidimensionality of the data, caused by the reciprocal interplay among the interacting regions. Along this line, the agent-based coevolutionary framework employing a distributed computational model and a distributed design mechanism, is particularly appropriate to facilitate brain modeling, explicitly addressing the specialties of brain areas [12]. Specifically, the implemented brain-inspired models consist of self-organized neural agents, each one representing a brain area. The collection of agents is designed and coordinated by means of a coevolutionary process. Previous studies demonstrated that the agent-based coevolutionary framework is capable of assigning distinct roles to substructures [13], facilitating the integration of partial models [15], and additionally enforcing the replication of results observed in biological studies [14]. Thus, the agent-based coevolutionary framework is particularly appropriate to support our current efforts.

In the following we present very briefly the agent-based coevolutionary framework. The interested reader is referred to [12], [13] for a more detailed description.

A. Computational Building Blocks

A collection of neural network agents are employed to represent brain areas. The present work extends the representation capabilities of the agent-based modeling of brain areas, by utilizing a set of different neural structures to model the components of the primate central nervous system. Similarly to previous works, we employ self-organized planar neural networks, but in addition to that in the present work we also employ recurrent MLPs [22] and Kohonen classifiers [21] to implement the components of the distributed model. The neural components of the model are properly linked by intermediate link structures, supporting the flow of information. As a result, any desired connectivity can be defined, simulating the connectivity of brain areas.

Kohonen networks are utilized to provide primitive visual skills to the model. The planar neural network is capable of developing a wide range of different functionalities due to the combination of excitatory and

inhibitory neurons interconnected with plastic Hebbian synapses. Thus, it is utilized to represent cortical areas of the parietal, temporal and frontal lobes. Finally, the non-adaptable recurrent MLP (its parametric specification is performed off-line and remains static during operation) is employed to represent the descending pathway of the Spinal Cord.

B. Design Mechanism

The specialized characteristics of neural agents are explored by a cooperative coevolutionary process. The brain modeling problem fits very well to cooperative coevolution, because separate coevolved populations can be used to make design decisions for each substructure representing a brain area, enforcing at the same time their successful integration in a global system.

Specifically, a Hierarchical Cooperative CoEvolutionary (HCCE) scheme is employed, being very effective in investigating the structure of large distributed systems being organized in gradually more complex groups of components [14],[15]. In short, two different kinds of populations encode either a Primitive agent Structure (PS) or a Coevolved agent Group (CG) consisting of components with common design objectives. The evolution of CG populations encoding assemblies of components, modulates partly the evolutionary process of its lower level PS populations enforcing 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. However, we stress the fact that the hierarchical nature of the coevolutionary design mechanism does not imply a hierarchical architecture to the model. The performance of partial structures can be either hierarchical or completely parallel. Hence, HCCE does not impose any constraints on simulating the connectivity of brain areas.

For details on the HCCE scheme the reader is referred to [12],[13],[14],[15]. In the following we provide only the details of the fitness assignment process, being necessary for understanding the underlying experimental setup.

For each PS or CG population p, a fitness function f_p is designed to drive its evolution. In particular, f_p is based on partial fitness functions $f_{p,t}$ evaluating the ability of individuals to serve the t-th task. Multiplication is used in order to combine fitness values laying in different ranges. Thus, the overall fitness is estimated by:

$$f_p = \prod_t f_{p,t} \qquad (1)$$

Furthermore, due to the randomized nature of coevolution, the cooperator selection process at the higher levels will probably select an individual encoding a component structure to participate in more than one complex assemblies. Let us assume that an individual participates in K assemblies which means that it will get K fitness values $f_{p,t}$. Then, the ability of the individual to support the accomplishment of the t-th task is estimated by:

$$f_{p,t} = \max_k \{ f_{p,t}^k \} \qquad (2)$$

where $f_{p,t}^k$ is the fitness value of the k-th solution formed with the membership of the individual under discussion. Following this mechanism fitness values representing the quality of complex solutions are propagated to the lower levels of the coevolutionary hierarchy, estimating the fitness of system components. The fitness assignment mechanism described above is very crucial for the successful convergence of the coevolutionary process.

V. Experimental Results

We now turn into the experimental process followed to model observation – execution activity in the primate brain. Our efforts are supported by embedding the model in a simulated humanoid robot that provides the adequate environmental interaction. Specifically, we employ an exact replication of the Fujitsu Hoap2 robot, running in the Webots simulation platform [11]. In the experiments described below, only the motion of the robotic arm is involved, that is based on a 3-DoF joint in the shoulder, and 1-DoF joint in the elbow. Appropriate physics properties were pre-programmed to the simulated robot to match the exact parameters of the real Hoap2.

As it is demonstrated in Fig. 1, the model consists of nine components. In particular, a Kohonen network supports primitive visual skills being able to distinguish different types of objects, seven planar cortical agents represent SPL, IPL, TmpC, PFC, PM, M1, S1 components, and one recurrent Multi-layer perceptron represents SC. The connectivity of these areas is supported by intermediate link structures.

The experimental process aims at reproducing existing biological data regarding the above mentioned areas during execution or observation of two different reaching behaviors. The first type of reaching –type A- direct the elbow to move vertically while remaining below the hand. The second type of reaching –type B- steers the elbow to be placed besides the hand, by moving laterally. Overall, four different partial tasks are employed regarding the execution E_A or observation O_A of reaching behavior type A, and the execution E_B or observation O_B of reaching type B.

A coevolutionary process is employed to specify the structural details of the model being able to accomplish all the four tasks. Separate populations (each one encoding candidate structures of a system component) are coevolved simultaneously, assembling the overall model. In particular, the model has been designed in two steps as it is described below.

A. Step 1. Acquiring Diverse Execution Capabilities

The first version of the model aims at accomplishing two different reaching behaviors by the robot. Two different objects are presented to the simulated robot (either a red ball, or a black cube) that have to be distinguished and reached in two different ways (type A reaching for the red ball, and type B reaching for the black cube). The successful accomplishment of tasks E_A and E_B

is evaluated based on the difference d_s of the desired and actual angles of robotic arm joints, at simulation step s:

$$d_s = (j_{s,1} - t_1)^2 + (j_{s,2} - t_2)^2 + (j_{s,3} - t_3)^2 + (j_{s,4} - t_4)^2 \quad (3)$$

where $j_{s,1}$, $j_{s,2}$, $j_{s,3}$, $j_{s,4}$, are the joint angles at the s-th time step and t_1, t_2, t_3, t_4 are the desired angle values. We note that previous brain studies confirm that motion guidance is performed on the basis of the joint angular error [17]. For each reaching type $i \in \{A, B\}$, separate total measures D_i are estimated, based on the sum of distances over all simulation steps:

$$D_i = \sum_s d_s \quad (4)$$

Following the formulation described by eqs (1) and (2) each population of the hierarchical scheme is evolved according to the following fitness function:

$$f = f_{E,A} \cdot f_{E,B} \quad \text{where}$$
$$f_{E,A}^k = 100 - D_A \text{ and } f_{E,B}^k = 100 - D_B \quad (5)$$

The coevolutionary process have run for 70 evolutionary epochs, providing a variety of partial models accomplishing successfully both reaching behaviors.

B. Step 2. Addressing Execution – Observation Biological Findings

In the second design step we additionally investigate the performance of the model in the case of observation. According to biological findings, the observing monkeys distinguish the type of reaching behavior, without trying to reproduce it (their arm is not moved), while similar but approximately 50% reduced activation patterns are deployed in the primary motor and somatosensory cortices during observation, as compared to execution. The current design step aims at refining the implemented model taking into account the above mentioned biological findings which must be computationally reproduced by the model.

The observation task of the robot is simulated as follows. We encode the trajectory followed by the robotic arm when the model operates in an execution mode. This is played back during observation, given as input to the sensor of visual motion. In that way, perfect visual observation input is assumed for the model, and additionally the problem of allocentric-egocentric transformation of visual information is avoided. Additionally, we assume that the arm of the demonstrator has different color than the arm of the observing robot, making their distinction possible during bootstrapping. Compared to biological experiments, this is a realistic working hypothesis since the monkey can easily distinguish its own arm from the arm of the human demonstrator (e.g. based on size, color, etc. information). This information is important for the set-up of the overall experiment, since the very same model should operate both in the case of execution and in the case of observation. Thus, the model develops an intrinsic way to determine its operating mode, be it observation or execution.

The current coevolutionary design procedure refines the model obtained in step 1, in order to meet biological findings. Specifically, the biologically relevant characteristics of the model are evaluated by the following quantitative criteria.

First, for each neuron j of M1 and S1, we estimate its average activation level both during execution $a_{E,i}^j$ and during observation $a_{O,i}^j$ for both types of reaching movements $i \in \{A, B\}$. In accordance to biological findings, the coevolutionary design process asks for neural modules with approximately 50% less activation during observation than during execution. The accomplishment of this objective is estimated quantitatively by the following measure:

$$H_i = \sum_{j, a_{O,A}^j < 0.6 a_{E,i}^j} a_{O,i}^j \quad (6)$$

The higher the value of H_i, the closer the observation activity of neurons to the half of execution activity.

Another issue for the model is that it should avert robotic arm motion during observation. This is not an easy to accomplish objective, because the recurrent nature of the model facilitates the emergence of motion orders for the robotic arm. It is noted that previous works in the area employed extra artificial components to prevent arm movements during observation [19].

For evaluating the observation of i-type reaching, $i \in \{A, B\}$ we use the measure M_i that is based on the total amount of robotic arm motion:

$$M_i = 50 - \sum_s (m_{s,1}^2 + m_{s,2}^2 + m_{s,3}^2 + m_{s,4}^2) \quad (7)$$

where $m_{s,1}$, $m_{s,2}$, $m_{s,3}$, $m_{s,4}$, are motion orders given to the four robotic arm joints, at observation simulation step, s. The higher the value of M_i the less the motion of the self-arm during observation of the i-th reaching behavior.

Following the formulation described by eqs (1) and (2) the coevolution of populations encoding the structure of system components is driven by the following fitness criteria:

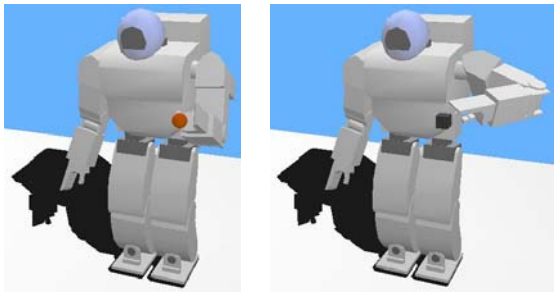
$$f = f_{E,A} \cdot f_{O,A} \cdot f_{E,B} \cdot f_{O,B}, \text{where}$$
$$f_{E,A}^k = 100 - D_A \quad f_{O,A}^k = H_A M_A \quad (8)$$
$$f_{E,B}^k = 100 - D_B \quad f_{O,B}^k = H_B M_B$$

Obviously, the redesign procedure aims both at executing successfully the two reaching behaviors, and additionally at observing them, mimicking aspects of mammalian brain functionality.

The hierarchical coevolutionary scheme reloads the results obtained in step 1, which are further evolved for 100 additional epochs, according to the global and partial fitness criteria described in equation (8). At the end of this procedure we obtain a variety of models that meet the design criteria. The performance of a sample model executing two different reaching behaviors is demonstrated in Fig. 2. Additionally, during observation the model successfully averts self-arm movements.

Furthermore, Figs. 3 and 4 demonstrate comparative results of execution vs. observation neural activation in M1 and S1, respectively. Obviously neural activation is approximately 50% reduced during observation, which is in accordance to biological findings. This fact additionally

demonstrates the capability of our approach to design complex distributed systems with brain-like functionality.



(a) (b)

Fig. 2. Robot performance during execution. Different objects are reached following different motion strategies.

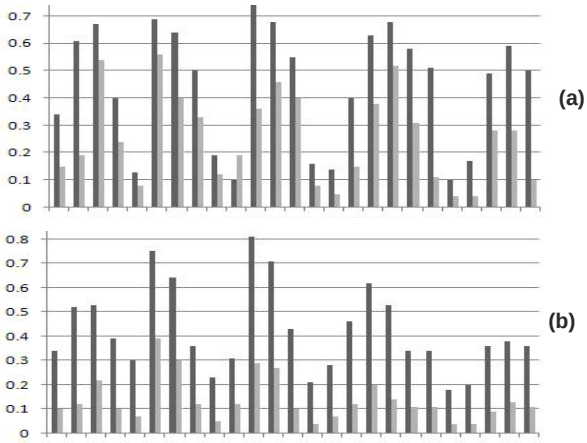


Fig. 3 Difference in M1 activation during execution (black) and observation (gray) of the first (a) and second (b) reaching behaviors. Each bar pair (black-gray) demonstrates average activity of a neuron.

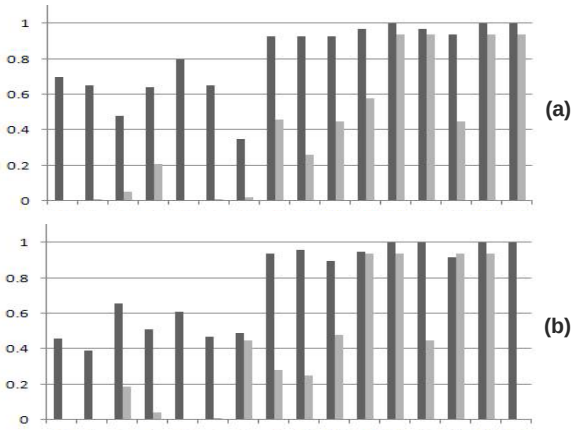


Fig. 4 Difference in S1 activation during execution (black) and observation (gray) of the first (a) and second (b) reaching behaviors. Each bar pair (black-gray) demonstrates average activity of a neuron.

C. Discussion

The experimental process described above demonstrates the development of a brain-inspired computational model mimicking how primate brain executes and observes reaching movements. In contrast to previous works in the field being concentrated on premotor mirror neurons, our model addresses overlapping observation – execution activity in a broader group of brain areas. Particularly, in accordance to recent biological findings [10], the model reproduces overlapping observation-execution activity in M1, S1. Furthermore, 50% reduced activation is found in both modules during observation, compared to execution.

Additionally, we stress the capability of the model to resolve bootstrapping conditions. This is necessary because both modes (observation/execution) should employ the very same computational structures during operation. Our model is capable of successfully distinguishing the two modes, developing the appropriate internal mechanisms preventing self-arm motion during observation. This is in contrast to previous works where the problem was either not dealt with [18], or it was partly addressed by an extra artificial component [19].

It is worth also emphasizing that the implemented model develops biologically relevant properties which are not explicitly specified in the fitness functions of the coevolutionary process. Specifically, the experimental setup described above does not specify anything about mirror neurons functionality in premotor cortex. Even though, after investigating the internal dynamics of the model we found premotor neurons that encode the different types of reaching behavior (either A or B). These neurons are activated both when the simulated robot observes and when it executes reaching. This functionality, being an emergent result of the coevolutionary process, is identical to the well known functionality of mirror neurons.

Some interesting observations and comments on the design process are also in turn. Specifically, we have initially tried to design the model exhibiting overlapping observation – execution activity, by running a single coevolutionary process identical to the one described in step 2, without however obtaining successful results. Our goal has been only accomplished when the refined model had previously acquired execution knowledge regarding the observed tasks (in the experiment described above, this is done in step 1). Intuitively, this fact agrees with the argument that primates-own experience is useful for understanding the observed actions [16]. In other words, the brain benefits from utilizing overlapping execution-observation systems, because the motion of others can be properly mapped on the preexisting behavioral knowledge of the observing subject in order to obtain meaning.

Finally, the experimental process described in the previous paragraphs demonstrates the beneficial characteristics of the agent-based coevolutionary framework being adequately powerful to address brain-modeling tasks. Specifically, this framework has been proved very effective in the current study, due to our need to address existing biological findings, and the complexity of the distributed model accounting more than 800 parameters.

VI. Conclusions

In the current work we develop a computational model

addressing the overlapping activity in primate's brain when animals execute a movement and when they observe a third subject performing the same movement. Brain imaging studies have shown the existence of a network of brain areas beyond the borders of premotor cortex, that shares the abovementioned execution-observation overlapping activity.

Our efforts aim at systematically considering biological findings in order to model and investigate this principle of brain functionality. Along this line, the current model takes into account biological findings showing that primary motor and somatosensory cortices are members of the network with the overlapping functionality, and additionally they exhibit 50% reduced activity during observation, compared to execution.

The modeling process is supported by the agent-based coevolutionary framework that is capable of designing complex distributed models integrating a variety of computational building blocks, and additionally enforcing the computational replication of related biological findings. The results obtained verify that this modeling approach effectively addresses the goals of the current study, integrating successfully in the same model building blocks with different operating characteristics.

Our future work will be directed towards subdividing parietal and premotor components to represent the brain architecture in more detail, capturing additional aspects regarding interaction of brain areas. Additionally, we aim at furnishing the model with learning capabilities and further utilize it as a major cognitive system for robots with observational learning skills. Fortunately, the agent-based coevolutionary framework with the inherent ability to refine existing models will support our efforts along these lines.

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