Ego-centric and Allo-centric Abstraction in Self-organized Hierarchical Neural Networks

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***Abstract*—The computational systems supporting the cognitive capacity of artificial agents are often structured hierarchically, with sensory-motor details placed in the lower levels, and abstracted conceptual items in the upper levels. Such an architecture mimics the structural properties of the animal and human nervous system.**

To operate efficiently in varying circumstances, artificial agents are necessary to consider both ego-centric (i.e. self-centered) and allo-centric (i.e. other-centered) information, which are further combined to address given tasks. The present work investigates effective assemblies for simultaneously placing ego-centric and allo-centric processes in the cognitive hierarchy, by evolving self-organized neural network controllers. The systematic study of the internal network mechanisms has showed that effective neural assemblies are developed by placing allo-centric information in the upper levels of the cognitive hierarchy, followed by ego-centric abstracted representations in the middle and finally sensory-motor details in the lower level. We present and discuss the obtained results considering how they are related with known assumptions about human brain functionality.

I. Introduction

The interaction of high-level cognition with the low level perceptual and motor primitives is a timely research topic involved in many aspects of intelligent systems' functionality. Such a hierarchical structuring is necessary to consider the conceptual abstraction of cognitive items related with both ego-centric and allo-centric information involved in the accomplishment of tasks.

Previous works investigating hierarchical cognition have mainly focused on the relationship between primary motor skills and complex behavioral sequences. For example, our previous work exploring the synthesis of complex behaviors by simple components revealed that not only the spatial connections between neurons but also the timescales of neural activity (i.e. fast or slow processing) may act as important mechanisms leading to a functional hierarchy [1]. Additionally, in a different experimental setup [2], [3], we have investigated the conceptual abstraction of behavioral rules, and their representation in neural network dynamics. Our findings suggest that separating high and low level processes in bottleneck neural architectures supports the functionality of the overall system, while rules can be effectively encoded as distinct attractors in the upper network level. Moreover, in a slightly different direction, research on multi-task learning neural networks, an approach aiming at internal neural representations that are shared by more than one tasks, has accomplished to effectively shape primary skills which are further synthesized to develop multiple complex behaviors [4], [5].

Besides the abstraction of self-referential information, intelligent systems are necessary to conceptualize environment specific characteristics. Previous works have investigated the encoding of allo-centric contextual information in the higher part of the cognitive system, which is used to adapt motor control in accomplishing varying versions of a given task. To address this issue, two main approaches have been followed, either by employing a set of small separate controllers each one specialized to a particular context [6], [7], or using a single global system that is parameterized on-line to address the specialized characteristics of a given context, an approach that has been greatly inspired by neuromodulation [8], [9].

Currently, the combination of ego-centric and allo-centric information has focused on transforming sensory values from one coordinate system to the other, making possible the extraction of qualitatively different informational items [10]. However, how ego-centric and allo-centric processes interact and what is the most appropriate arrangement when they are placed in the cognitive hierarchy is not sufficiently explored. This is the topic of the present work.

In particular, we investigate the joined abstraction of ego-centric and allo-centric concepts in a single artificial neural network. This is accomplished by considering a task that involves two different behavioral rules (the ego-centric information), which are applied on three environments with different structural characteristics (the allo-centric information). Such an experiment is expected to provide insight on possible mechanisms for effectively combining ego-centric and allo-centric information in hierarchical systems. In short, our findings show that ego-centric information is encoded closer to the low level perceptual and motor primitives, while allo-centric environment specific information is represented in the uppers parts of the cognitive hierarchy.

The rest of the paper is organized as follows. In the next section we describe the experimental setup used in our study. Then we present the obtained results focusing on the ego-centric and allo-centric mechanisms self-organized in the neural network. Finally, in a detailed discussion we consider how the obtained results compare to known assumptions about human consciousness related to the interaction of ego-centric

Fig. 1. A schematic representation of the response rules. The robot starts always from the bottom of the T-maze. Light cues are shown as double circles. Target locations are represented by $\times$, while reward corresponds to the gray area.

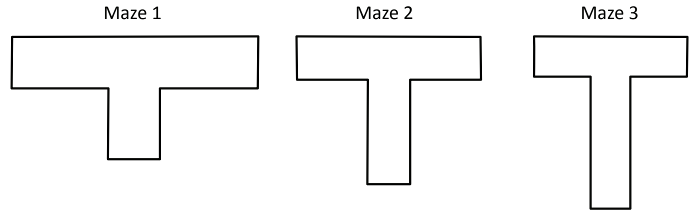

Fig. 2. A schematic representation of the three different types of T-maze environments considered in the delayed response task.

and allo-centric processes.

II. Experimental Setup

The current study is an extension of our previous works [2], [3] addressing the manipulation of behavioral rules, in a mobile-robot interpretation of the classical Wisconsin Card Sorting (WCS) task [11]. The current work aims to investigate the scaling of conceptualization, investigating how artificial agents, apart from behavioral rules, categorize and conceptualize alternative environments each one having distinct spatial characteristics. Specifically, we test the combination of two behavioral rules with three different environments, resulting in six different operating circumstances.

A. Behavioral Rules

The investigated task is inspired by the rat version of WCS, exploring rodents' rule switching capacity [12]. We assume that a mobile robotic agent is located at the bottom of a T-maze environment (see Fig. 1). At the beginning of a trial, a light cue appears at either the left or the right side of the robot. Depending on the light side, the robot has to move to the end of the corridor, making a 90^o turning choice towards the left or right. The side of the light is linked to the choice of the robot according to two different cue-response rules. The first is called Same-Side (SS) rule, implying that the robotic agent should turn left if the light source appeared at its left side, and it should turn right if the light source appeared at its right side. The second rule is named (OS), implying that robot should turn to the side opposite of the light.

The capacity of the agent to follow rules SS and OS is evaluated by testing long sequences of response trials. For example, assume that a human experimenter selects rule SS as the correct rule for a given sequence of trials. Based on the side of the light cue, the experimenter provides properly positioned rewards to the side of the T-maze that the robot should turn (see Fig. 1). Every time that the robot gives a correct response, it reaches the target location driving to a reward area that indicates it follows the right rule. In the case that the agent does not receive reward, it should switch the adopted rule.

B. Environment contexts

In order to minimize the effect of embodiment in the abstraction and representation of rules we have investigated the accomplishment of the delayed response task in three different T-maze environments, each one having distinct characteristics (see Fig. 2). In the first T-maze, the corridor is short and wide, in the second maze the corridor has medium length and width, while in the third the corridor is long and narrow. The experiments considered in the present study, focus on CTRNN controllers that can accomplish rule following in all three environments.

The above described experimental setup is expected to minimize the effect of embodiment in the abstraction and representation of high level cognitive processes. Additionally, the combination of the two rules with the three maze types is expected to enforce representing, at least partially, both the environment-invariant characteristics of rules, as well as the rule-invariant characteristics of the environments. In that way, the current setup aims to explore effective schemes for implementing and coordinating ego-centric (i.e. rule) and allo-centric (i.e. environment) information.

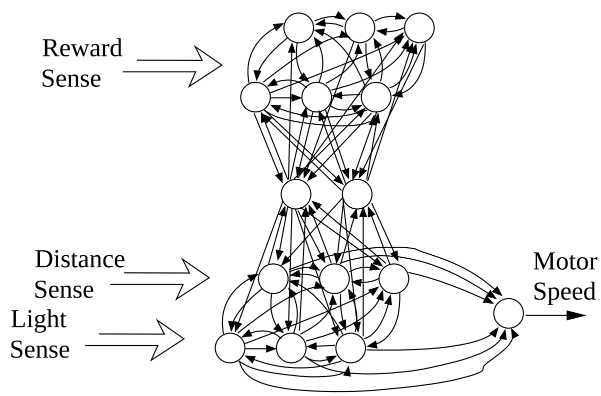

Fig. 3. Schematic representation of the bottleneck CTRNN used in the current study.

C. The Neural Network Controller

We use a Continuous Time Recurrent Neural Network (CTRNN) model [13] to investigate SS and OS rule following in three different maze environments. All CTRNN neurons are governed by the standard leaky integrator equations described in previous studies [14], [15]. CTRNNs implicitly represent high level knowledge to guide behavior, using internal neuro-dynamics. Thus, the state of the controller is initialized only once at the beginning of the first trial, and then neuronal dynamics continues without resetting until the end of the task. Following our previous work [2] showing that bottleneck

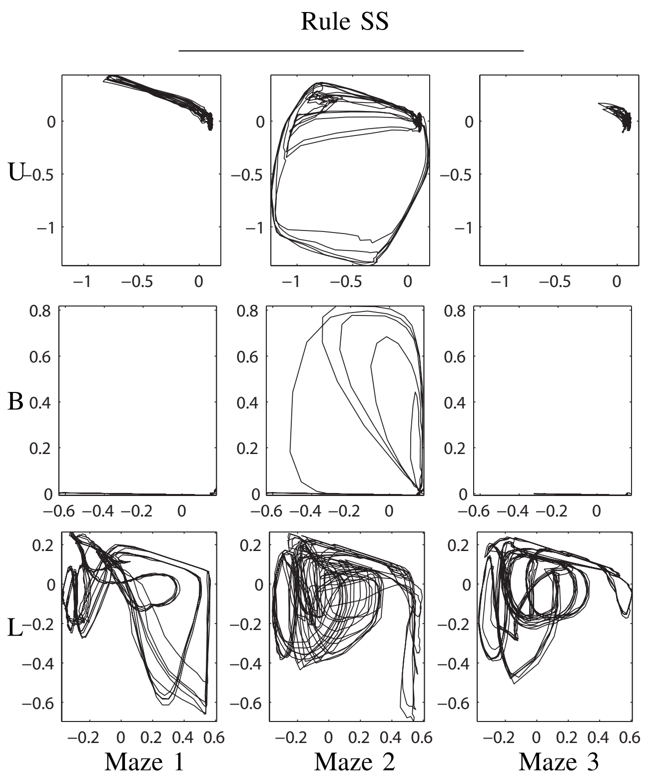

Fig. 4. Phase plots of neural activity in the upper (U), bottleneck (B) and lower (L) level of the CTRNN, when the agent follows the SS rule. Plots in different columns correspond to different T-maze environments. For each plot, the x-axis and y-axis correspond to the first and second principal component respectively.

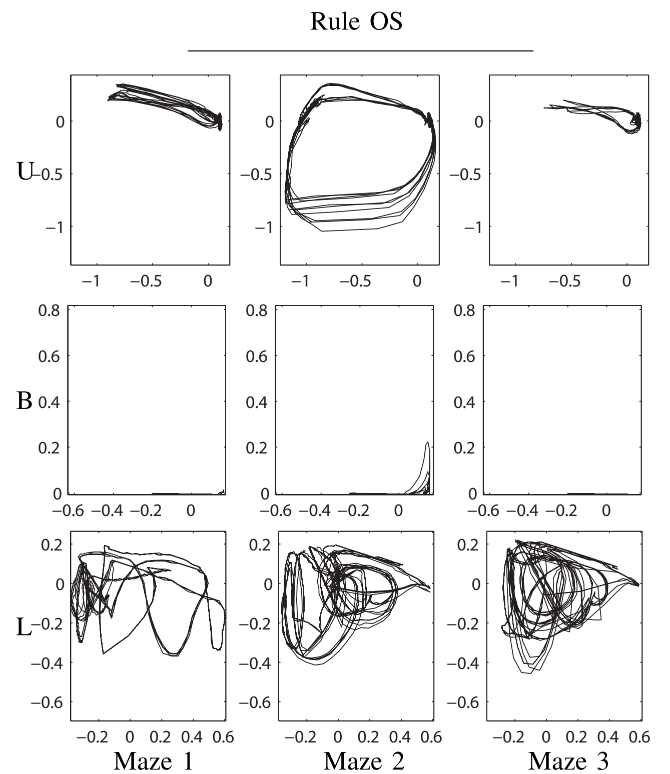

Fig. 5. Phase plots of neural activity in the upper (U), bottleneck (B) and lower (L) level of the CTRNN, when the agent follows the OS rule. Plots in different columns correspond to different T-maze environments. For each plot, the x-axis and y-axis correspond to the first and second principal component respectively.

configurations are more effective in accomplishing rule following tasks compared to fully connected CTRNNs, the current work employs a bottleneck structured network. As shown in Fig 3, we use two bottleneck neurons to separate CTRNN levels accepting different types of sensory information. The bottleneck neurons loosely segregate information processing in each level, maintaining minimum interactions between them, therefore facilitating the development of high and low level cognitive skills in the corresponding parts of the CTRNN.

In order to investigate how embodied activities are linked with the high-level representation of rules and environment contexts, we employ a two wheeled simulated robotic agent equipped with 8 uniformly distributed distance, light and reward sensors. The connectivity of sensory information with the different layers of the CTRNN is also shown in Fig 3. The details of input-output connectivity are similar to [16] and they are omitted here due to space limitations.

D. Evolutionary Procedure

We use a Genetic Algorithm (GA) to explore cognitive dynamics enabling artificial agent to respond successfully for all six combinations of rules and environments. In short, we use a population of artificial chromosomes encoding CTRNN controllers (their synaptic weights and neural biases). Each candidate solution encoding a complete CTRNN is tested on six different tasks, each one examining the ability of the agent to respond successfully in one of the six different combinations of rules and environments. The performance of the agent is evaluated separately for each task, and the obtained measures are subsequently aggregated in a global fitness value that guides artificial evolution. Further details on the evolutionary procedure are omitted here due to space limitations.

III. Results

We have evolved CTRNN controllers running ten different GA processes. Four of the evolutionary procedures converged successfully configuring CTRNNs capable of adopting rules SS and OS, responding successfully in all three environments. Interestingly, the results obtained from the statistically independent evolutionary procedures exhibit common internal dynamics, which are discussed below using as a working example one representative solution.

We are interested to explore what kind of information is encoded in each part of the CTRNN. To address this issue, we conduct principal component analysis (PCA) and we take the phase plots of the first two principal components of neural activity in the upper, bottleneck and lower part of the CTRNN, as shown in Figs 4 and 5. We observe that in the lower level six distinct attractors are shaped, each one corresponding to a particular rule-environment pair. In the bottleneck level, the first principal component is mainly active, regulating the interaction between the upper and lower level of the network.

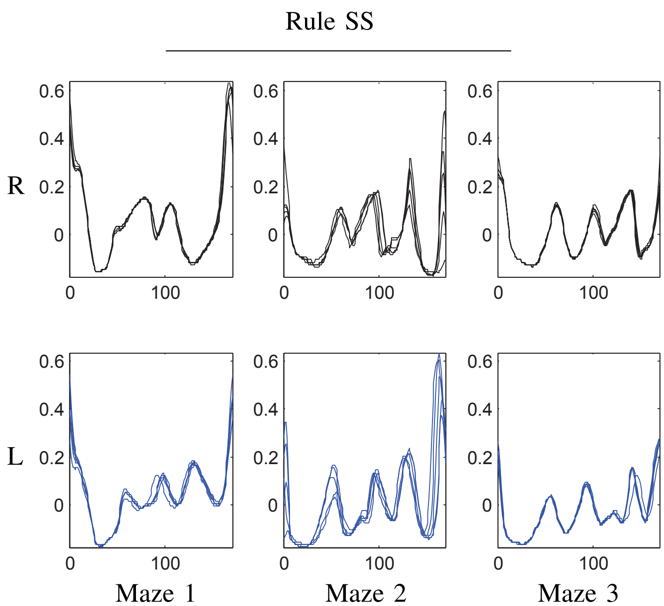

Fig. 6. The activity of the first principal component of the bottleneck neurons in ten indicative trials when the agent follows the SS rule, turning either right (R), or left (L). Plots in different columns correspond to different T-maze environments.

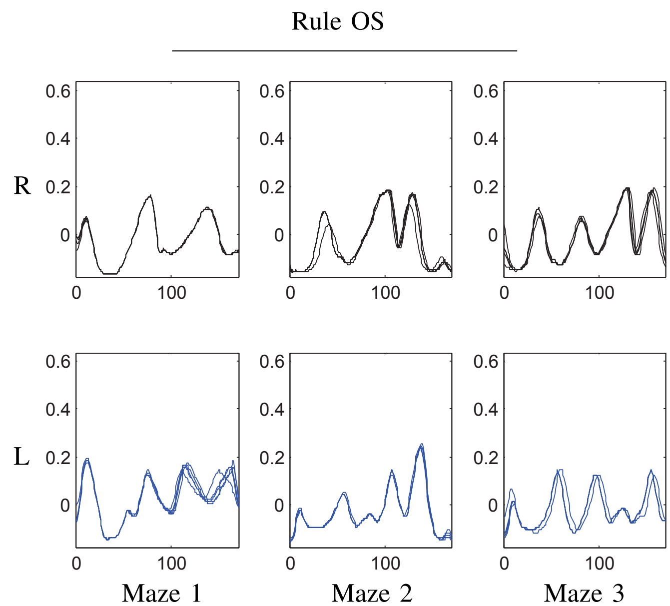

Fig. 7. The activity of the first principal component of the bottleneck neurons in ten indicative trials when the agent follows the OS rule, turning either right (R), or left (L). Plots in different columns correspond to different T-maze environments.

In the upper level, the trajectories of neural activity are clearly grouped in three pairs of shapes corresponding to the three different types of T-mazes (i.e. the activity corresponding to Maze1 has nearly the same shape for both the SS and OS rules). Interestingly, the maze-shaped attractors in the upper level are partially modulated by the particular rule adopted by the agent. For example, the Maze2 attractors shown in Figs 4 and 5 in the second plot of the first line, are both circular with different radii.

It is interesting to note the partial overlap between the phase plots of a given neural network level, in Figs 4 and 5. These overlaps facilitate transitions from one mental state to the other, enabling the artificial agent to successfully perform in all rule-environment combinations. This is because at the beginning of a task, the agent is not aware of the correct response rule, or the current environment type. Therefore, it is necessary to test and assess alternative choices in order to discover the operating framework for a given task (set by the experimenter). The overlap of phase plots enables the agent to easily change back and forth its environment and rule choice, as well as the choice of turning left or right. In our previous works [2], [16], we have systematically examined switching between higher level states represented by partially overlapping attractors and thus, in the current work we omit this topic due to space limitations. In short, the inability of the agent to receive reward in the case of a non-successful response causes instability to the attractor represented state, making the CTRNN jump into a new attractor, that corresponds to a new mental state.

Besides the encoding of the environment type in the upper part of the CTRNN, we explore how the agent encodes the adopted rule. Figs 4 and 5 does not show any clear evidence on the internal representation of rules. To obtain insight on this issue we focus on the early and late simulation steps of trials which should be properly linked to facilitate tracking of rules along consecutive robot responses. We explore the bottleneck neurons, conducting PCA analysis of their activity. The first principal component of neural activity when the agent turns left or right, is shown in Figs 6 and 7 for the case of the SS and OS rule respectively. In these plots, we observe that the bottleneck activity starts and ends at relatively high values when rule SS is followed, while it starts and ends at low values when rule OS is adopted. This activation difference is used for preserving rule information when passing from one trial to the other, enabling the agent to follow a particular rule for a long sequence of trials. It is noted that examining upper and lower CTRNN activity with a similar PCA procedure does not show any systematic differentiation between SS and OS, suggesting that the active rule is mainly encoded in the bottleneck neurons.

Finally we explore inferencing of the robot moving direction in the response trials. This is an important issue because for all rules and all environments, the agent has to undertake common decisions, driving both left-wards and right-wards. Given, that the high-level and bottleneck neurons are mainly involved in environment-type and rule encoding respectively, we focus on neural activity at the lower level which is practically responsible for implementing the given response as a sequence of motor commands. After performing principal component analysis on the activity of the lower level, we observe that the third principal component (PC3) encodes the direction of robot's response at the beginning of the trial. This is shown in Figs 8 and 9, depicting PC3 unfolding for left and right robot

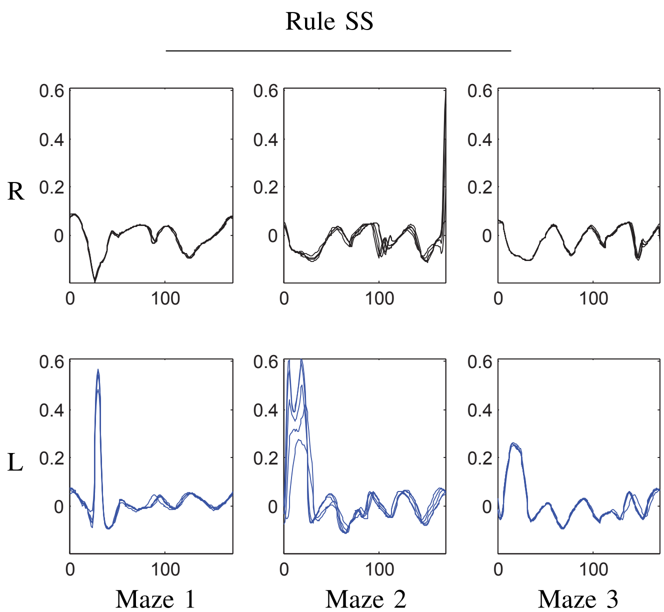

Fig. 8. The activity of the third principal component (PC3) of the lower level neurons in ten indicative trials when the agent follows the SS rule, turning either right (R), or left (L). Plots in different columns correspond to different T-maze environments.

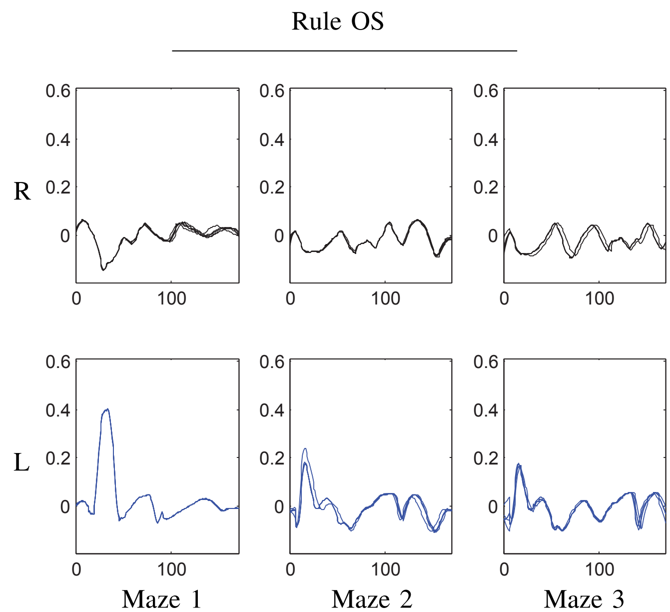

Fig. 9. The activity of the third principal component (PC3) of the lower level neurons in ten indicative trials when the agent follows the OS rule, turning either right (R), or left (L). Plots in different columns correspond to different T-maze environments.

responses. Clearly, in the first 40 simulation steps of trials, PC3 values rise up when the robot decides to move right-wards, while PC3 values reduce when the robot moves left-wards. This observation applies for all six rule-environment combinations, which means it is not affected by the adopted rule, or the environment type. Interestingly, the first and second principal component does not appear correlated with the rule, the environment type, or any other high-level aspect of the problem, and they seem to deal with the wall-avoidance issues related with a particularly directed response. In particular, any time the robot is approaching an object, an automatic turning to the opposite direction is triggered to avoid bumping.

Overall, the obtained results show that the upper level is involved in categorizing and conceptualizing environment specific information, that is external to the artificial agent, which implies it is processing allo-centric information. The middle level is related with the rule-following strategy guiding agent's behavior, therefore maintaining an abstracted form of ego-centric information. Finally, the lower level of the cognitive hierarchy that is in direct contact with the sensors and effectors of the agent considers the motor details of the particular actions, implementing primary motor skills which are properly activated to facilitate navigation.

We would like to note that the rather simple behavioral nature of the investigated tasks is in contrast to the sufficiently complex high-level issues addressed in our experiments. This approach facilitates the study of the internal mechanisms self-organized in the CTRNN, revealing the structural details of the ego-centric and allo-centric conceptualization on-top of primary motor skills. Besides the fact that the investigated tasks involve rather simple behaviors, the qualitative characteristics of the observed results may sufficiently scale for more complex perceptual and behavioral capacities, as it is discussed in the following section (see how CTRNN dynamics compare to allocentric-egocentric interface theory of consciousness).

IV. Discussion

The present study aims to investigate the principles of ego-centric and allo-centric hierarchical functioning in cognitive systems, by evolving self-organized neural controllers for artificial agents. In particular, we have explored the conceptual abstraction of self-referential behavioral strategies as well as the abstraction of environment specific contextual information in the same CTRNN controller. Our findings suggest that the cognitive hierarchy is structured in a way that encodes information with more ego-centric characteristics in the lower levels, which are abstracted in less detailed ego-centric representations in the next levels, turning to allo-centric information in the upper levels of the cognitive hierarchy. In other words, there is an gradual transformation from ego-centric to allo-centric information as we move to the higher levels of cognition.

In the above described hierarchical structuring, the information concerning environment context is encoded in the upper level of the cognitive hierarchy (i.e. being far from low-level motor details), besides the fact that the characteristics of the environment are in direct link with the sensory-motor details affecting the implementation of a particular response. More specifically, in the current experiment, the agent capitalizes on the wall avoidance dynamics implemented in the lower levels of the hierarchy. The motion plan provides the general direction to the robot (either left-wards, or right-wards), which is combined with the innate wall avoidance dynamics in order to implement the desired robot behavior. In other words, the characteristics of the environment are not directly linked with response representation. The categorization of environment types may have a different usability in our experiments, that seems to be related with the selection and the tracking of rules. According to our results, the agent gives higher priority in identifying allo-centric information, i.e. the current type of the T-maze environment, and then explores the available behavioral strategies to select the correct response rule. That is the agent first clarifies the external context, and then considers motion strategy and the particular implementation.

We would like to note that we have also conducted experiments aiming to address the problem investigated in the present study by adding one more layer in the CTRNN, without however observing significant changes in the internally self-organized neurodynamics. In particular, the encoding of rules remains in the bottleneck neurons, with both other layers on top being involved in the handling of environment specific contextual information.

The internal mechanisms observed in the self-organized CTRNN models are in agreement with the "Allocentric-Egocentric Interface (AEI) Theory of Consciousness" [17] arguing that as we move in gradually higher levels of cognition, the representation of information is less and less centered around the self, integrating gradually more allo-centric characteristics.

Moreover, it is argued that the cognitive processes in the lowest and highest levels may be operated unconsciously, while those serving as the interface of high and low level cognition are the ones gathering the highest amounts of consciousness. Investigating this assumption for our model, we observe that the lower level of the CTRNN operates reactively any time it approximates an object, turning to the opposite direction. This means that the robot does not need to direct attention on corridor navigation to avoid bumping on the walls. Our results does not show any clear evidence about handling the environment-type in a less conscious way, however this could be a valid assumption for our CTRNN controllers given that environment type is decided only once, early in the experimental trial and then it is not changing for the rest of the task.

Interestingly, in the obtained results, the rule representation located in the middle of the cognitive hierarchy seems to modulate the activity in both the lower and the upper layers of the CTRNN (e.g. environment representations between Figs 4 and 5 are slightly different, while the rule clearly directs robot's moving direction shaped in the lower level of the controller). According to AEI theory, this characteristic (i.e. the modulation of other layers activity) corresponds to the type of information that is most consciously manipulated by the agent, and this is typically encoded in the middle of the cognitive hierarchy. This working principle seems valid for our results, explaining why rules are encoded in the middle of the cognitive hierarchy. Specifically, the adopted rule must be repetitively combined with the provided light cue in order to develop the correct delayed response in each trial, which means that the agent should regularly and actively use rule information to accomplish all six tasks.

Overall, the mechanisms self-organized internally in the CTRNNs provide support to the AEI hypothesis as a valid explanation of hierarchical cognitive processes that combine ego-centric and allo-centric information.

V. Conclusion

The proposed work aims to explore how the low level motor details linked to the particular embodied instantiation of the cognitive system interact with the conceptual abstraction of behavioral strategies and the environment specific contextual information. According to our results, the cognitive processes form a hierarchy of mental representations with egocentric representations placed below allo-centric representations. This observation suggests that part of what it means to be lower or higher in the cognitive hierarchy is to be closer to or further from the sensory and motor periphery of the nervous system.

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