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Time Experiencing by Robotic Agents

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Abstract. Biological organisms perceive and act in the world based on spatiotemporal experiences and interpretations. However, artificial agents consider mainly the spatial relationships that exist in the world, typically ignoring its temporal aspects. In an attempt to direct research interest towards the fundamental issue of time experiencing, the current work explores two temporally different versions of a robotic rule switching task. An evolutionary process is employed to design a neural network controller capable of accomplishing both versions of the task. The systematic exploration of neural network dynamics revealed a self-organized time perception capacity in the agent's cognitive system that significantly facilitates the accomplishment of tasks, through modulation of the supplementary behavioural and cognitive processes.

1 Introduction

Sensing the flow of time is fundamental for intelligent organisms [1]. Especially for humans that live in large societies having complex daily schedules, time perception is essential for almost every activity we engage in. Subjective time is an intrinsic indicator of how long external events should last, often functioning as an error signal leading to specific action selection. Despite the essential role of time in natural cognition, current endeavours in developing intelligent robots are by no means directed towards encompassing time perception in the systems' repertoire of capacities. The majority of robotic research focuses on task accomplishment such as navigating to reach goals, or moving objects around, with only superficial investigation of time perception issues (for example, tracking systems monitor speed changes across time, but this is far from considering the flow of time). The inability of artificial systems to experience the temporal characteristics of events hinders their understanding about the real, dynamic world.

In order to explore how time perception is involved in artificial cognition, the current study explores two time-differentiated versions of a behavioural-rule switching task. In particular, a simulated robotic agent has to consider unpredictably changing reward signals, in order to switch between response rules choosing the one that is considered correct at a given time [2]. We investigate the behaviour of the agent for a sequence of trials assessing its ability to successfully switch among rules. We study two temporally different versions of the aforementioned task exploring how rule switching interacts with perceiving the temporal characteristics of the given problem. In the first version, all trials have equal predefined durations, while in the second version the temporal length of trials is determined in a dynamical manner based on agent's behaviour. We evolve Continuous Time Recurrent Neural Network (CTRNN) controllers capable to accomplish both versions of the rule switching task. Subsequently, we study the mechanisms self-organized in the CTRNN. We observe that the controller monitors the temporal characteristics of the task, a process that plays an important role in the rule following/switching.

In the following sections, we describe the experimental setup followed in the present study, the obtained CTRNN results, and how the latter compare to the time perception processes of the human brain.

2 Experimental Setup

The current study is an extension of our previous works [2, 3], addressing rule switching in a mobile-robot interpretation of the classical Wisconsin Card Sorting (WCS) task [4].

The Neural Network Controller. We use a CTRNN model [5] to investigate the role of duration perception and how it interacts with rule switching. Following our previous work [2] showing that bottleneck configurations are more effective in rule switching tasks compared to fully connected CTRNNs, the current work employs a bottlenecked network. Intuitively, the loose separation of the network facilitates the development of low level and high level skills in the corresponding parts of the CTRNN. The details of input-output connectivity are similar to [3] and they are omitted here due to space limitations.

Mobile Robot Rule Switching Task. The investigated task is inspired by the rat version of WCS, exploring rodents' rule switching [6]. 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 each rule is evaluated by testing sequences of the above described trials. For example, assume that a human experimenter selects rule SS and asks the agent to follow it for several trials. Based on the side of the light cue, the experimenter provides reward 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. At a random time (unknown to the robotic agent), the experimenter changes the rule considered correct, positioning rewards according to the OS rule. Thus, the robot that is not aware of this change will give an incorrect response, being unable to get a reward. This is an indication that the adopted rule is not correct anymore. The agent is necessary to discover this rule change, switching its response strategy according to the new rule. This will make the agent receiving rewards again, indicating that the correct rule is followed.

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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 ×, while reward corresponds to the gray area.

At some later time the experimenter will switch the rule again, and so on. The above described rule following/switching process is repeated for 10 times.

Trial Duration. In order to investigate artificial mechanisms of duration perception, we have implemented two temporally different versions of the underlying rule switching task. In particular, in the first version we let the controller to dynamically specify the duration of trials (i.e. all trials end as soon as the robot reaches the target location at a distance of 10 units). We call this version of rule switching *Dynamic Trial Duration (DTD)*. In the second version, all trials have the same duration during the whole task (i.e. the trial ends after a predefined number of steps, irrespective to the agent's reaching of the target location). This version is called *Static Trial Duration (STD)*. In order to avoid the possibility that the DTD timing will self-organize in an identical form with STD, we have explicitly differentiated the two scenarios by letting the DTD last "at most 170 steps", while the STD lasts "exactly 190 steps".

Evolutionary Procedure. We use a Genetic Algorithm (GA) to explore how rule switching capacity and duration perception self-organize in CTRNN dynamics. 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 tasks examining the ability of the network to switch between rules in both the DTD and the STD setup.

3 Results

We have evolved CTRNN controllers running ten different GA processes. Five of the evolutionary procedures converged successfully configuring CTRNNs capable of rule switching. 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.

The performance of the agent's rule switching during DTD and STD is demonstrated in Fig. 2. During trials 1-4 the agent follows SS rule, successfully acquiring rewards. Next, in trial 5 the experimenter changes rule to OS. The agent that is not aware of this change fails to accomplish reward for one trial in the DTD case and for two consecutive trials in the STD case. In forthcoming trials the agent successfully follows OS. The rule is changed again in trial 15, where the agent is missing the reward for one trial in both the DTD and the

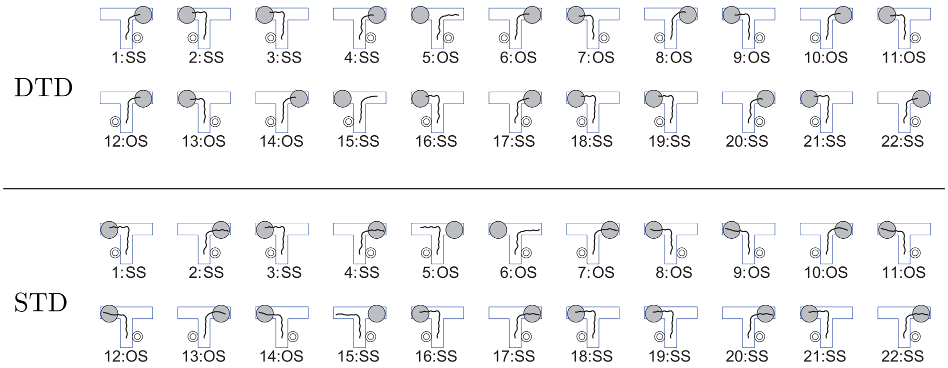

Fig. 2: The response of the agent in 22 consecutive trials covering three phases, for the case of DTD and STD setups. The robot initially follows SS rule, then it switches to OS, and back to SS.

STD case. This time the agent switches quickly back to SS, receives a reward in trial 16, and continues responding according to SS for the rest of the trials.

After investigating the internal dynamics of the controller among trials, we observed much slower dynamics in the higher part of the bottlenecked CTRNN compared to the fast fluctuation of the lower level neurons. This finding is similar to [3], implying that the higher part of the controller is mainly involved in encoding the rule that is currently adopted by the robot, while the lower part is responsible for applying the rules considering also environmental interaction issues (e.g. wall avoidance). In the following we restrict our discussion to the higher level neurons of the CTRNN exploring how rule manipulation interacts with time perception. In order to place activation difference between the DTD and STD cases within a general and systematic framework, we have conducted a Principal Component Analysis (PCA) on the activity of higher level neurons.

The first two principal components of higher level activity during DTD task with the robot turning left or right following either OS or SS are shown in Fig. 3. Note that the agent has to memorize rules when passing from one trial to the next. The value of principal components at the beginning and ending of trials provide insight in the rule encoding approach. In Fig. 3 we can easily observe that the second principal component (PC2) supports memorizing the currently adopted rule because for OS trials PC2 starts and ends from relatively low values, while for the case of SS trials, the same principal component starts and ends from relatively high values. Thus, PC2 differentiates OS and SS by tracking the currently adopted rule between consecutive trials.

Turning to the STD version of the task, the first two principal components of higher level activity for all possible cases are depicted in Fig. 4. We can easily observe that the two rules are now differentiated based on PC1. In particular, for both the left and the right turnings of OS, PC1 starts and ends at rather high values, while for the case of SS rule, PC1 starts and ends at low values.

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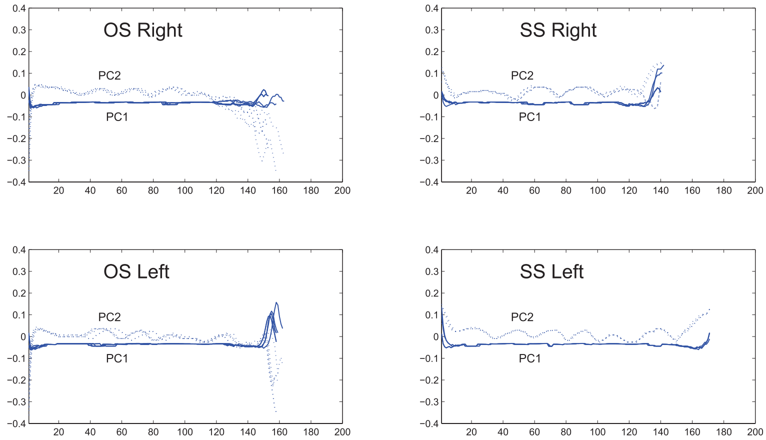

Fig. 3: The activity of the first two principal components in a set of multiple DTD trials. Principal component 1 (PC1) is demonstrated with a solid line, while principal component 2 (PC2) is demonstrated with a dotted line. Clearly, rules SS and OS are separated based on the second principal component, PC2.

Overall, CTRNNs encode the temporal characteristics of tasks in the principal components of neural activity, a mechanism that plays an important role in memorizing the rule that is currently adopted by the artificial agent.

Discussion. In the human brain, imaging studies propose that time perception may emerge from the integration of interoceptive afferent activity (body sensations) in the insular cortex [7, 8], an area of the brain which is also strongly involved in emotional awarenes and in complex decision making, therefore sharing the same neural substrate with other behavioural and cognitive capacities. Similarly, in our study the primitive time perception ability of CTRNN's is integrated with the rule following/switching capacity.

Interestingly, there is an open neuroscience debate regarding the existence or non-existence of two distinct neural mechanisms involved in processing sub-second and supra-second time intervals [9]. Despite this is not the main topic of the present study, the mechanism self-organized in our work may bridge the two opponent arguments, suggesting that sub-second and supra-second mechanisms may rely on different principal components of the same overall system, therefore being partially but not fully segregated.

4 Conclusions

In the field of artificial cognitive systems, time perception remains a largely unexplored issue. The current study shows that considering time may significantly support artificial cognition. Our work is an early attempt towards a systematic exploration of the time perception capacity in the context of autonomous

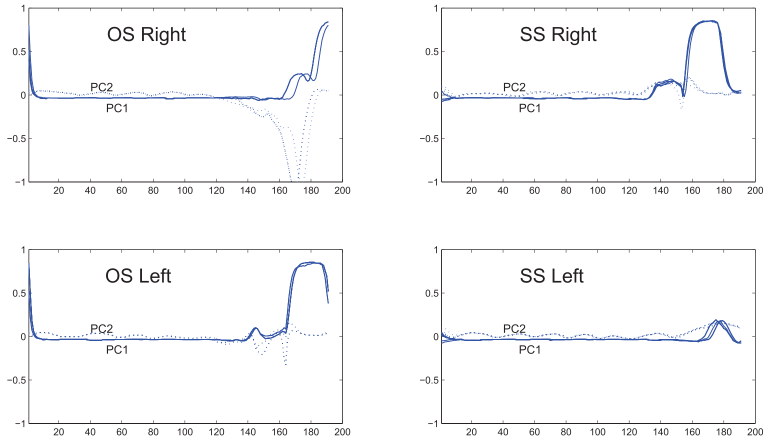

Fig. 4: The activity of the first two principal components in a set of multiple STD trials. Principal component 1 (PC1) is demonstrated with a solid line, while principal component 2 (PC2) is demonstrated with a dotted line. Clearly, rules SS and OS are now separated based on the first principal component, PC1.

intelligent systems. In the future, we plan to explore additional aspects of time perception, focusing on duration estimation and duration calculus, considering the neurocognitive mechanisms underlying human skills in the temporal domain.

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