Self-organized Neural Representation of Time

Michail Maniadakis and Panos Trahanias

Foundation for Research and Technology - Hellas, ICS, Greece
{mmaniada,trahania}@ics.forth.gr

Abstract. Time is crucially involved in most of the activities of humans and animals. However, the cognitive mechanisms that support experiencing and processing time remain largely unknown. In the present work we follow a self-organized connectionist modeling approach to study how time may be encoded in a neural network based cognitive system in order to provide suggestions for possible time processing mechanisms in the brain. A particularly interesting feature of our study regards the implementation of a single computational model to accomplish two different robotic behavioral tasks which assume diverse manipulation of time intervals. Examination of the implemented cognitive systems revealed that it is possible to integrate the main theoretical models of time representation existing today into a new and particularly effective theory that can sufficiently explain a series of neuroscientific observations.

1 Introduction

Over the last few decades, an increasing number of studies have demonstrated the accuracy with which animals and humans are able to estimate time. However, the exact cognitive mechanisms that enable the measurement of time remain largely unknown. Broadly speaking, there are two main theories explaining how our brain represents time [1,5]. The first is dedicated models (also known as extrinsic, or centralized) that assume clock-like mechanisms and thus yield an explicit metric of time. This is the oldest and most influential explanation on interval timing. The models included in this category employ mechanisms that are designed specifically to represent duration. Traditionally such models have followed an information processing perspective in which pulses that are emitted regularly by a pacemaker are temporally stored in an accumulator [4,3]. This has inspired the subsequent pacemaker approach that uses oscillations to represent clock ticks [13]. The Striatal Beat Frequency (SBF) model is the most famous example of this category, assuming that timing is based on the coincidental activation of basal ganglia neurons by cortical neural oscillators [12]. Other dedicated models assume monotonous increasing or decreasing processes to encode elapsed time [16,15]. The second category includes intrinsic models (also known as distributed) that describe time as a general and inherent property of neural dynamics [7,2]. According to this approach, time is intrinsically encoded in the activity of general purpose networks of neurons. Thus, rather than using a time-dedicated neural circuit, time coexists with the representation and processing of other external stimuli.

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Besides the human devised representations of time that have been discussed above, our brain may actually use a different approach to encode and process time. Self-organized computational modeling can serve as a complementary means to explore representational schemes [14], and thus facilitate convergence in the time representation debate. This is the aim of the present study which employs a robotic experimental setup to investigate alternative schemes of time representation. Interestingly, the perception and processing of time remains particularly unexplored in the field of robotic systems [9]. Given the essential role of time in nearly all our daily activities, research in the emerging branch of robotic time perception is expected to significantly contribute in the seamless integration of artificial agents into the heavily time-structured human societies.

In the present study, we consider two different time processing tasks namely Duration Comparison and Past Characterization, which are accomplished by the very same robotic cognitive system. This is in contrast to the time representation schemes mentioned above, which have been discussed in a theoretical basis without being associated to the accomplishment of specific tasks. More specifically, a Continuous Time Recurrent Neural Network (CTRNN) [10] is used to develop an "artificial brain" for the robotic agent. We use an evolutionary design procedure based on Genetic Algorithms to search possible configurations of the artificial brain that can accomplish the afore mentioned tasks. Subsequently, we study the mechanisms self-organized in the CTRNN to extract the characteristics of effective time perception mechanisms that may be also valid for interval processing in our brain. The obtained results showed that very effective neural schemes can be used for generating, representing, and processing time, by combining the key characteristics of the "dedicated and intrinsic theories of time".

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 processing data of the brain.

2 Experimental Setup

The current study is an extension of our previous works [10,11,9], investigating time perception and processing mechanisms by artificial agents. While these works have focused on single tasks, the present study simultaneously addresses two different tasks with temporal characteristics in order to emphasize the generalization of the self-organized time processing mechanisms.

Due to space limitations, in the following we will mainly concentrate on the presentation of the tasks, describing very briefly the robotic agent and its connectivity to the Continuous Time Recurrent Neural Network that have been already presented in detail in [10,11].

The Robotic Agent. We simulate a two wheeled mobile robot equipped with 8 uniformly distributed distance, light and sound sensors. The distance sensors are mainly used during navigation to avoid robot bumping on the walls. The light sensor is used to receive a task-indicator informing the robot which one of the tasks is considered at a given experimental session. The sound sensor is

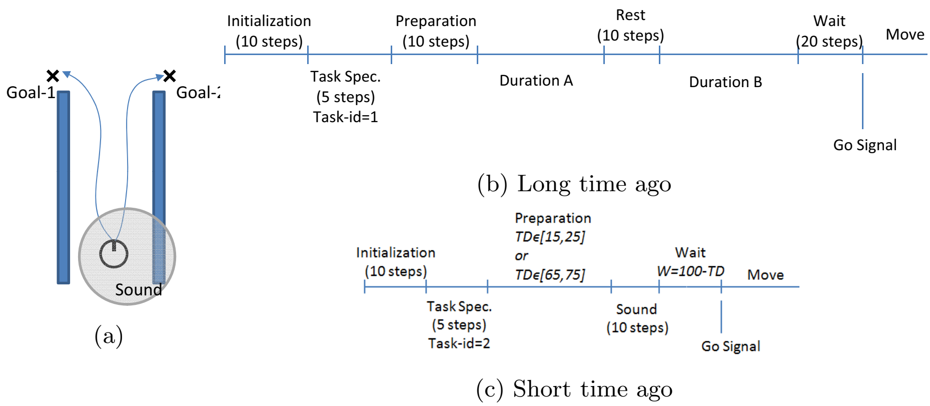


Fig. 1. Part (a) shows the experimental environment used in our study. Part (b) summarizes the experimental procedure followed in the Duration Comparison experiment. Part (c) summarizes the experimental procedure followed in the Past Characterization experiment.

used for the perception of temporal durations (i.e. the robot must perceive the duration of emitted sounds). The robotic cognitive system is implemented by a Continuous Time Recurrent Neural Network (CTRNN) similar to [10,11].

Duration Comparison. The scenario of this task assumes that the robot perceives two time intervals A and B, compares their duration and drives to the end of the corridor turning either to the left side in the case that A was shorter than B, or, to the right side in the case that A was longer than B (see Fig 1 (a)). The experiment starts with the simulated agent located at the bottom of the corridor environment. The robot remains at the initial position for a short initialization phase of 10 simulation steps, where it experiences a light cue indicating that the experimental procedure for the Duration Comparison task will follow (see Fig 1 (b)). Subsequently, after a short preparation phase, the agent experiences two sounds having temporal durations A and B, both of them randomly specified in the range $[10, 100]$. The two sounds are separated by a predefined rest period of 10 simulation steps. Just after sound B, the agent is provided 20 simulation steps to compare A and B, decide which one was longer and prepare its motion strategy. At the end of this period the robot is provided a “go” signal and it starts navigating across the corridor. In order to successfully complete the task, the agent has to navigate to the end of the corridor and turn right in the case that A interval was longer than B, or, turn left in the case that A interval was shorter than B.

Past Characterization. In this task, it is assumed that the robot experiences a sound and at a future time it judges whether this particular experience was at a short or long time ago. Similar to the previous task, the robot responds by driving along the corridor and turning either to the left side in the case that the sound event happened a long time ago, or, to the right side in the case that the event sound happened a short time ago (see Fig 1 (a)).

The experiment starts with the simulated mobile robot located at the beginning of the corridor. After a short initialization period, the agent experiences a light cue indicating that the experimental procedure that will follow, concerns the Past Characterization task (see Fig 1 (b)). Subsequently, after a preparation interval with duration $TD \in [15, 25]$ for the case that the sound event was long time ago in the past, or $TD \in [65, 75]$ in the opposite case, the agent experiences a sound for a period of 10 steps. Then a wait period follows that is dynamically specified as $W = 100 - TD$ (i.e. the pair of TD and W, determines whether the sound experience of the agent has been in the short or long past). At the end of the wait period the agent is provided a "go" signal and it starts navigating towards the end of the corridor. If the sound experience was in the long past the agent must turn left, while if the sound experience was in the short past, the agent must turn right.

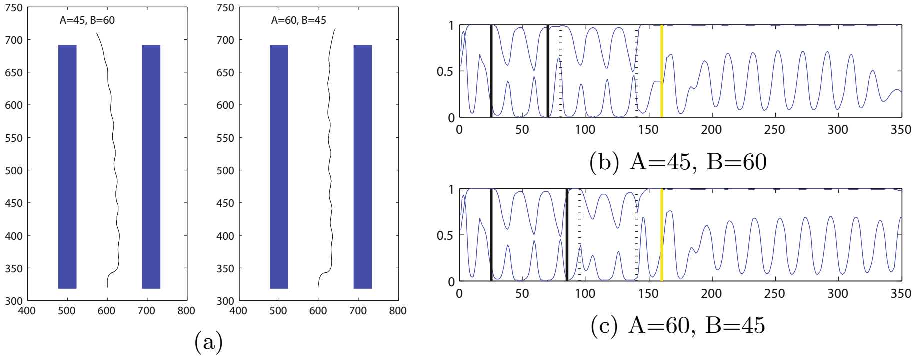
Performance Evaluation. To evaluate the response of the artificial agent in both the Duration Comparison and the Past Characterization task, we mark two different positions in the environment which are used as goal positions for the robot, as shown in Fig 1 (a). Depending on whether Goal1 or Goal2 is considered correct in a given experimental session, we measure the minimum distance D, between the agent's path and that goal position. Additionally, during navigation, we consider the number $Bumps$ of robot bumps on the walls. Thus, the success of the robotic agent to a given experimental session $i \in \{A > B, A < B,\}$ and $j \in \{LongPast, ShortPast\}$ is estimated by:

$$S_i = S_j = \frac{100}{D \cdot (Bumps + 1)} \tag{1}$$

By maximizing $S_{A>B}$, $S_{A<B}$ and $S_{LongPast}$, $S_{ShortPast}$ we aim at minimizing the distance from the goals therefore produce responses at the correct side of the corridor, as well as avoid bumping on the walls. The total capacity of the robot to accomplish the Duration Comparison and the Past Characterization task is estimated by considering robot's perfornace in all four possible cases as:

$$FIT = S_{A>B} \cdot S_{A<B} \cdot S_{LongPast} \cdot S_{ShortPast} \tag{2}$$

Evolutionary Procedure. We use a Genetic Algorithm (GA) to explore possible time perception and processing mechanisms in CTRNN-based cognitive systems. In short, we use a population of artificial chromosomes encoding possible CTRNN configurations (their synaptic weights and neural biases). Each candidate solution encoding a complete CTRNN is tested on both the Duration Comparison and the Past Characterization task, evaluated according to equation (2). The scores accomplished by the controllers are used to sort and evolve the population of chromosomes, therefore producing the next generation of candidate solutions. During reproduction, the best 30 individuals of a given generation mate with randomly selected individuals using single point crossover, to produce the next generation of CTRNNs. Mutation corresponds to the addition of up to 25% noise, in the parameters encoded to the chromosome, with each parameter having a probability of 4% to be mutated. This iterative evolutionary procedure is repeated for a predefined number of 500 generations.



(a) (b) A=45, B=60 (c) A=60, B=45

Fig. 2. Part (a) shows the performance of the agent when comparing two time intervals with lengths A=45, B=60 and A=60, B=45. Part (b) shows the activity of two CTRNN neurons that are actively participating in the measurement and comparison of A=45, B=60. Part (c) shows the activity of the same neurons for the case of A=60, B=45. In both plots the first two black vertical solid lines indicate the A period, and the next pair of black vertical dotted lines indicate the B period. The yellow line corresponds to the time that the "go" signal is given to the robot.

3 Results

We have evolved multiple CTRNNs running ten different GA processes. Five of the evolutionary procedures converged successfully configuring CTRNNs capable of processing time. 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.

Duration Comparison. The agent can successfully perceive and compare pairs of random temporal durations. The performance of the robot for two time intervals A and B with interchangeable durations 45 and 60 simulation steps is demonstrated in Fig 2(a).

We have examined the activity of CTRNN neurons to reveal the time processing mechanisms self-organized in the network. We observed that all CTRNN neurons are governed by oscillatory dynamics. This is in agreement to the dedicated-time models that assume oscillatory activity to implement a clock-like tick mechanism [3] that facilitates duration perception. However, besides the fact that the task is clearly separated into two distinct phases of (i) perception and (ii) action, some neurons remain active in the whole duration of the task which implies that time perception is mixed with the ordinary cognitive activity (i.e. neurons are not "dedicated" to time).

Additionally, neurons are not passively oscillating but seem to encompass crucial temporal information. In particular, Fig 2(b) show the activity of two neurons for the case of $A < B$ in Fig 2(a), and Fig 2(c) shows the activity of the same neurons for the case o $A > B$ in Fig 2(a). In both plots the amplitude of the oscillation increases as long as the agent experiences either interval A or B and thus, the difference between the two neurons is constantly decreasing in relation to the length of the experienced duration. In other words, the amplitude of the oscillation can be actively used for counting the elapsed time. This observation extends the ideas behind the oscillatory models of time, suggesting that oscillations may not serve as passive ticks, but they might be actively involved in measuring time. Our results agree to both the oscillatory [12,13] and ramp [15] models, suggesting that the two mechanisms can be effectively integrated into the very same cognitive system and should not be considered as contradictory.

Another interesting observation regards duration resetting when turning from the A interval to the B interval. Typically, dedicated models assume a full reset of perceived duration, while intrinsic models assume no-reset [8]. According to our results, a reset-counting mechanism is activated by the end of A, because the amplitude of the oscillation of the two neurons at the end of A, is higher than the amplitude of the oscillation at the beginning of B. This is in agreement to the dedicated approach. However, in both Fig 2(b) and (c), time perception neurodynamics at the begging of A is different than that at the beginning of B. This suggests that the activity of neurons prior to the observation of a given duration affects the way that the network experiences the flow of time. In other words, the length of A affects the way that B is experienced, which is in agreement with the intrinsic representation of time [7]. This observation suggests a new type of duration resetting, which stands in the middle of the full reset and no reset. According to our results, it is possible for cognitive systems to use a dynamic resetting mechanism where the length of A determines the initial state during the perception of B. For example, when A is long the amplitude of the oscillation during perception of B starts from relatively low values (see Fig 2(b)), but when A is short the amplitude of the oscillation during perception of B starts from relatively high values (see Fig 2(c)).

The last observation additionally suggests that the amplitude of the oscillation is correlated with the likelihood that the currently observed duration will be judged as the longest in the experimental session. In other words, after experiencing a long A interval, in the early steps of B observation it is unlikely that B will be judged longer and the amplitude of the oscillation is low. As time progresses and the length of B increases, the probability that B will be considered longer is rising and thus the amplitude of the oscillation is also increasing. This mechanism explains how the robot decides whether A or B has been actually longer. It is noted that a similar observation with probabilistic information integrated into time-relevant neural activity has been also observed in macaque's brain [6] significantly enhancing the biological reliability of the mechanism revealed from our results.

Past Characterization. In this task, the robot characterizes the temporal distance of a given sound cue, as being either a short or long time ago. The behavior of the robot is shown in Fig 3 (a). In the first case, the robot experiences a sound 73 steps prior to the "go" signal while in the second case the robot experiences a sound 25 steps prior to the "go" signal. The agent successfully characterizes the two signals, driving to the end of the corridor and then turning left in the case of long time ago, but right in the case of short time ago.

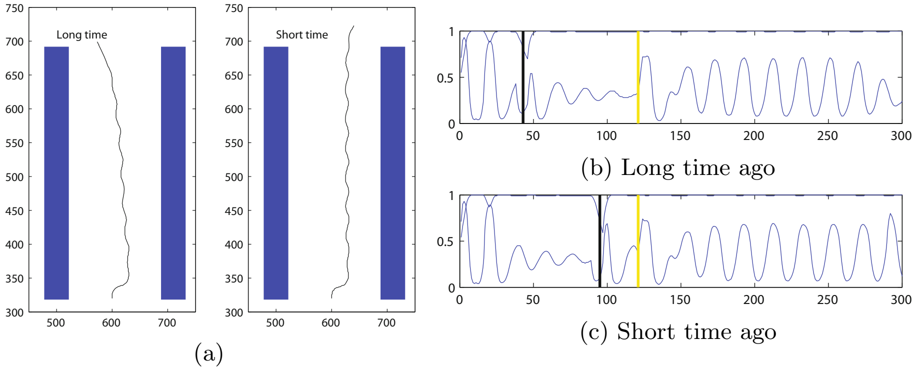


Fig. 3. Part (a) shows the performance of the robot when experiencing a sound cue "long time ago" and "short time ago". Parts (b) and (c) show the activity of the CTRNN neurons depicted also in Fig 2 for each one of the two cases in part (a). In both plots, the time of sound experiencing is indicated with a black vertical line. The yellow line corresponds to the time that the "go" signal is given to the robot.

Examining the internal activity of the CTRNN in Fig 3 (b) and (c), we observe that every time the sound is experienced, both neurons are temporally activated and subsequently, the one remains silent, but the other continues to oscillate with a constantly decreasing amplitude. Since amplitude effectively measures time duration, it is evident that a counting-down mechanism has been implemented in the CTRNN. While in the Duration Comparison task the amplitude of the oscillation was increasing as long as the sound cue was present, reverse counting does not require any sensory input and this mechanism is used for measuring the distance to a past sensory cue. In other words, when the amplitude is small then it has been a long time ago since the last experience of sound, but when the amplitude is large then it has been a short time since the last presentation of sound (i.e. there has been not enough time for the amplitude to decrease). Clearly, the observed neurodynamics suggest again that oscillatory activity may be not only used as a passive ticking mechanism but it is likely that they actively participate in the accomplishment of the task.

4 Discussion and Conclusions

To the best of our knowledge, none of the existing approaches for time representation can provide mechanisms that simultaneously explain the accomplishment of the two tasks discussed in the present study. The self-organized CTRNN dynamics considered in our work have revealed multiple points for bridging the currently contradictory theories into a new enhanced scheme with more explanatory power. More specifically, our results suggest that:

– Interval timing can be encoded in the activity of neurons supporting ordinary cognitive tasks.

– Oscillations can effectively facilitate the estimation of the elapsed time and the amplitude of the oscillatory activity may be used for accumulating duration (i.e. we may not need separate subsystems for ticking and counting).
– Active rather than passive oscillatory activity may underpin the implementation of time processing mechanisms in a range of different tasks.

In conclusion, the present work adopts a computational approach to investigate time representation in cognitive systems, suggesting the integration of time-representation approaches existing today. At the same time, the current work brings to the surface the issue of temporal cognition that remains largely unexplored in the field of autonomous artificial systems. In the future we intend to explore how time processing may facilitate robotic agents to accomplish tasks in the highly time-structured human environments.

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