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Robotic interval timing based on active oscillations

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Abstract

Interval timing is crucially involved in many of the daily activities of humans and animals. However, the cognitive mechanisms enabling the encoding and processing of time in the brain remain largely unknown. In the present work, we follow a self-organized modeling approach to study unconventional representations of time in neural network based cognitive system. 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. The examination of the implemented cognitive system revealed that it is possible to integrate the two main theoretical models of time representation existing today - the dedicated and intrinsic representations - into a new theory that effectively combines their key characteristics.

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Keywords: Robotic time perception; Duration comparison; Duration reproduction; Self-organized modelling

1. Introduction

The processing of duration is one of the most common tasks performed by humans. However, our knowledge on how time is encoded in the brain is still very limited. Broadly speaking, there are two main approaches that explain how our brain represents time (Bueti, 2011; Ivry & Schlerf, 2008). The first is the dedicated approach that assumes 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 and nothing else. Traditionally such models follow an information processing perspective in which pulses that are emitted regularly by a pacemaker are temporally stored in an accumulator (Droit-Volet, Meck, & Penney, 2007; Gibbon, Church, & Meck, 1984; Woodrow, 1930). This has inspired the subsequent pacemaker approach that uses oscillations to represent clock ticks (Large, 2008; Miall, 1989). Other dedicated models assume monotonous increasing or decreasing processes to encode elapsed time (Simen et al., 2011; Staddon & Higa, 1999). The second approach includes intrinsic explanations that describe time perception as an inherent property of neural dynamics (Dragoi,

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Staddon, Palmer, & Buhusi, 2003; Karmarkar & Buonomano, 2007). According to this approach, rather than using a time-dedicated neural circuit, time is intrinsically encoded in the activity of general-purpose networks of neurons that support other cognitive tasks. An attempt to combine the two approaches is provided by the Striatal Beat Frequency (SBF) model which assumes that timing is based on the coincidental activation of basal ganglia neurons by cortical neural oscillators (Matell & Meck, 2004; Meck, Penney, & Pouthas, 2008). The SBF model assumes a dedicated timing mechanism in the basal ganglia that is based on monitoring distributed neural activity in the cortex.

Besides the human devised time-representations 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 novel representations of time in neurocomputational systems (Ruppin, 2002). This is the approach followed in the present study. More specifically, to investigate unconventional schemes of time representation, a robotic experimental setup is employed to perform an unbiased exploration of alternative time representations. A Continuous Time Recurrent Neural Network (CTRNN; Beer, 1995; Maniadakis, Trahanias & Tani, 2009) is used to develop an "artificial brain" for a robotic agent that accomplishes two different duration processing tasks, namely duration comparison and duration reproduction. We use an evolutionary design procedure based on Genetic Algorithms to search possible configurations of the artificial brain that accomplish the two tasks. Subsequently, we study the mechanisms self-organized in the CTRNN to extract the characteristics of time perception and processing mechanisms.

The obtained results showed that active, imperfect oscillations that incorporate temporal information and are also involved in non-temporal tasks, may be used to effectively experience and process time in neurocomputing systems. We use the term "active" to highlight the difference of the mechanism observed in the current study from the typical passive and perfectly shaped oscillations that have been used so far for the dedicated representation of time (coupled with a separate mechanism that counts oscillations). Interestingly, the active nature of the observed oscillatory activity incorporates a counting-like mechanism for time and blends time perception with behavior execution. This assumes oscillatory activity to play a more complex role that goes beyond the passive perception of time therefore bridging the dedicated and intrinsic representations of time.

An early report on our robotic experiments (Maniadakis & Trahanias, submitted) has mainly focused on short durations in the range of few seconds, demonstrating also that the proposed representation exhibits the scalar characteristics that are typical observed in biological timing mechanisms (Lejeune & Wearden, 2006). This paper presents a new set of experiments that explore the ability of active oscillations to process intervals in the range of a few tens of seconds. This enhances further the validity of the integrated scheme combining the key characteristics of the intrinsic and dedicated theories in a new enhanced scheme of time representation.

The rest of the paper is organized as follows. In the next section, we describe the technical details of the approach adopted in the present study discussing the: robotic simulated environment, neural network architecture, behavioral tasks, and evolutionary procedure that searches for effective time representations. The following section presents the results of our experiments highlighting the key characteristics of the new, self-organized time representation. The last section contrasts our findings to the current interval timing literature.

2. Experimental Method

2.1. Simulation environment

We have implemented a simulation of a two wheeled mobile robot equipped with 8 uniformly distributed distance, light, and sound sensors. The distance sensor is mainly used during navigation to avoid robot bump on the walls. The light sensor is used to receive a task-indicator informing the robot which one of the three tasks is considered at a given moment of the experimentation. The sound sensor is used for the perception of temporal durations (i.e., the robot must perceive emitted sounds).

The robot operates in a rather simple environment with two walls located in its left and right side (Figure 1). The robot has to perceive the duration of sound cues and drive without bumps along the corridor that is shaped by the two walls, behaving as requested by the scenario of the particular task.

Given that the experiments considered in the present study do not require complex manipulations of moving objects, we set one simulation step of the environment to correspond to 100 ms. Therefore, a real world behavior expressed for 10 s corresponds to 100 simulation steps in the virtual environment considered in the present study.

2.2. Continuous Time Recurrent Neural Network.

A three-level CTRNN (Beer, 1995; Maniadakis, Trahanias & Tani, 2009) is used to provide the artificial agent with behavioral and cognitive capacities. The network consists of 4 neurons in the upper level, 6 neurons in the middle level, and 4 neurons in the lower level. Full intra- and inter-level connectivity is assumed in the network. All sensory information is projected only in the middle level of the CTRNN. This allows different functional roles to be developed in each layer of the network. Synaptic weights are determined by an evolutionary procedure (see below) and they remain constant during task testing.

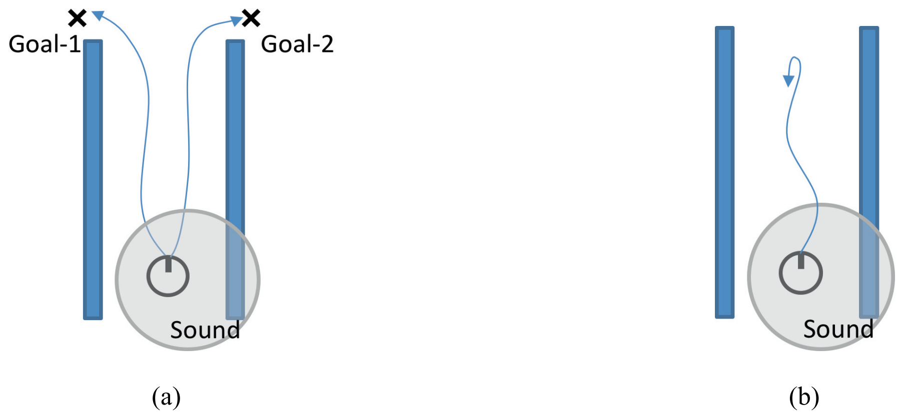


Figure 1. A graphical representation of the experimental setup. The robot is depicted as a small circle in the bottom of the corridor. Depending on the task, the robot is asked to either reach one of the two goal positions, as shown in part (a), or make a sudden 180^0 turning, as shown in part (b).

2.3. Behavioral Tasks

To explore time representation schemes through artificial neural network self-organization, the present study considers two different time processing tasks, which are described below.

Duration Comparison. The task assumes that the robot perceives two time intervals A and B, compares them 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 Figure 1a). The task starts with the simulated mobile robot located at the beginning of the corridor environment. The artificial agent 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 Figure 2). 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 the A interval was longer, or, turn left in the case that the A interval was shorter (than B).

To evaluate the response of the artificial agent we mark two different positions in the environment, which are used as goal positions for the robot, as shown in Figure 1(a). Depending on whether A has been actually longer than B or not, we select the correct goal position and we measure the minimum distance *D,* between the agent's path and that goal position (i.e., when A<B the agent should approximate Goal1, but when A>B the agent should approximate Goal2). Additionally, during navigation, we consider the number *Bumps* of robot bumps on the walls. Overall, the success of the agent to a given duration comparison $i \in \{A > B,\ A < B\}$ is estimated as:

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

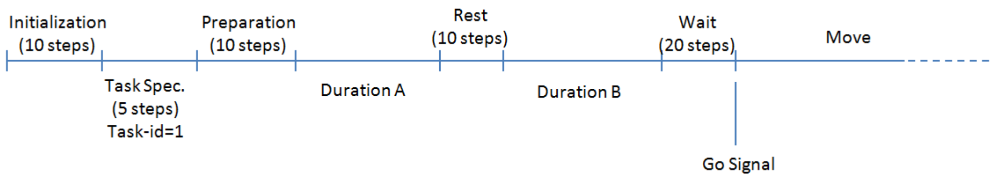


Figure 2. The structure of the Duration Comparison experiment.

By maximizing $S_{A>B}$ and $S_{A<B}$ 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 task considering both possible relations between A and B intervals, is estimated as:

$$FIT_{DC} = S_{A>B} \cdot S_{A<B} \quad (2)$$

Duration Reproduction. The experiment assumes that the robot perceives a time interval A and reproduces its duration by moving forward for the same amount of time. As soon as the robot believes that the duration of A has been completely reproduced it makes a quick 180^o turning that indicates the end of reproduction (see Figure 1b).

The experiment starts with the 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 Duration Reproduction task (see Figure 3). Subsequently, the agent experiences a sound with temporal duration A, that is randomly specified in the range [10, 100]. Just after this sound, the agent is provided 20 simulation steps to prepare its behavioral response. Then, the agent is provided a "go"' signal and it starts navigating towards the end of the corridor. In order to successfully complete the task, the agent has to move forward navigating freely inside the corridor, for a time interval that equals to A. As soon as the robot believes that the A interval has been completed, it has to make an immediate turn of 180^o degrees, and continue navigation facing the bottom of the corridor.

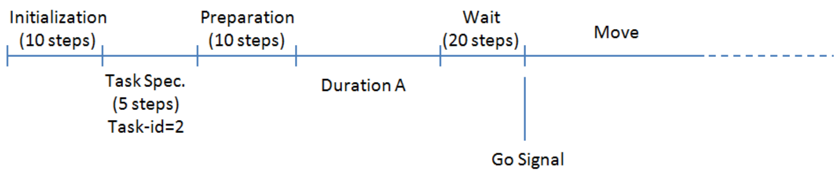


Figure 3. The structure of the Duration Reproduction experiment.

To evaluate the response of the artificial agent we consider its motion direction in the whole period of duration reproduction. To enable the robot express the 180^o turning we examine robot's behavior for A+30 simulation steps. In particular, during the reproduction of the A interval, the robot must move mostly forward, which means its direction should be around 0^o degrees. Just after the completion of the A and for the next 30 steps, the robot must turn to the opposite direction driving at 180^o degrees. Therefore, the success of the agent on the duration reproduction task is numerically evaluated by:

$$FIT_{DR} = \frac{1}{\sum_{1}^{length(A)} Dir^2 + \sum_{length(A)+1}^{length(A)+30} (180 - Dir)^2} \quad (3)$$

By maximizing FIT_{DR}, we aim at minimizing the difference between robot moving direction and the optimal moving direction as it is explained above.

2.4. Evolutionary Design

We employ a Genetic Algorithm (GA; Nolfi & Floreano, 2000) to explore possible cognitive mechanisms that enable the artificial agent to perceive and process time accomplishing the three behavioral tasks described above. In particular, we use a population of 1000 artificial chromosomes each one encoding a different CTRNN configuration. Each candidate CTRNN solution is tested on a randomly initialized version of the three tasks. To estimate the time processing capacity of a particular CTRNN configuration, we combine the metrics associated with the three tasks:

$$F = FIT_{DC} \cdot FIT_{DR} \qquad (6)$$

This is the fitness measure that drives the evolutionary exploration of CTRNN configurations. By maximizing F, we get artificial cognitive systems that can successfully accomplish all three tasks considered in the present study. We use a standard GA process with survival of the fittest individual along consecutive generations. Real-value encoding is used to map synaptic weights and neural biases of the CTRNN into chromosomes.

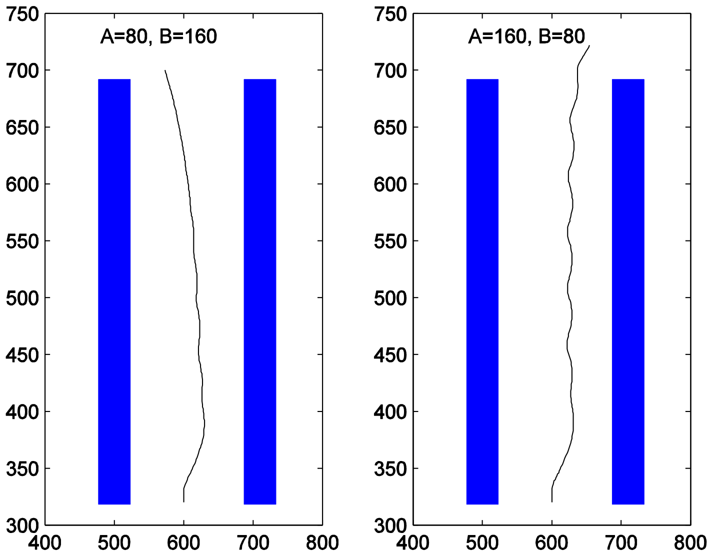


Figure 4. The responses provided by the robot in the two cases of the Duration Comparison task.

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. Crossover facilitates transferring knowledge from one generation to the next. Mutation corresponds to the addition of up to 25% noise, in the parameters encoded to the chromosome, with each CTRNN parameter having a probability of 4% to be mutated. Mutation facilitates the exploration of new, gradually more effective solutions. In all evolutionary runs the randomly initialized population is evolved for a predefined number of 500 generations.

3. Results

We have conducted statistically independent evolutionary runs to explore possible neural mechanisms that are capable to accomplish the two duration processing tasks. In order to obtain insight into the representation of time self-organized in the evolved robot brains, we have investigated the characteristics of neural activity in the CTRNN. Interestingly, all obtained results show (qualitatively) similar neurocomputational mechanisms, which are described below.

Duration Comparison. To assess the duration comparison capacity of the obtained CTRNN configurations, we have tested multiple pairs of random durations. In all cases the robot could robustly perceive the duration of intervals, compare their length, and finally respond successfully by driving to the side of the corridor that corresponds to the longest interval. The behavior of the robotic agent when comparing two time intervals with duration 8 and 16 secs (that correspond to 80 and 160 simulation steps) is shown in Figure 4.

The neural activities of the CTRNN for the two instances of the duration comparison task considered here, are shown in Figures 5 and 6. Each subplot corresponds to one of the three layers of the CTRNN. In all 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.

In all layers of the CTRNN the activity of neurons is governed by oscillatory dynamics. This is particularly useful from a time representation perspective, because oscillations provide a means for measuring time intervals (i.e. by counting the number of oscillations) as it is suggested by dedicated timing representations (Large, 2008; Meck et al., 2008). At the same time, from a robot control perspective, the amplitude of oscillatory dynamics enable steering the robot in the desired direction. Therefore, oscillating mechanisms seem particularly appropriate to support both the cognitive and the behavioral requirements of the time-based behavioral tasks. This is in support to the theories suggesting the correlation of time perception with embodiment (Craig, 2009; Wittmann, 2009).

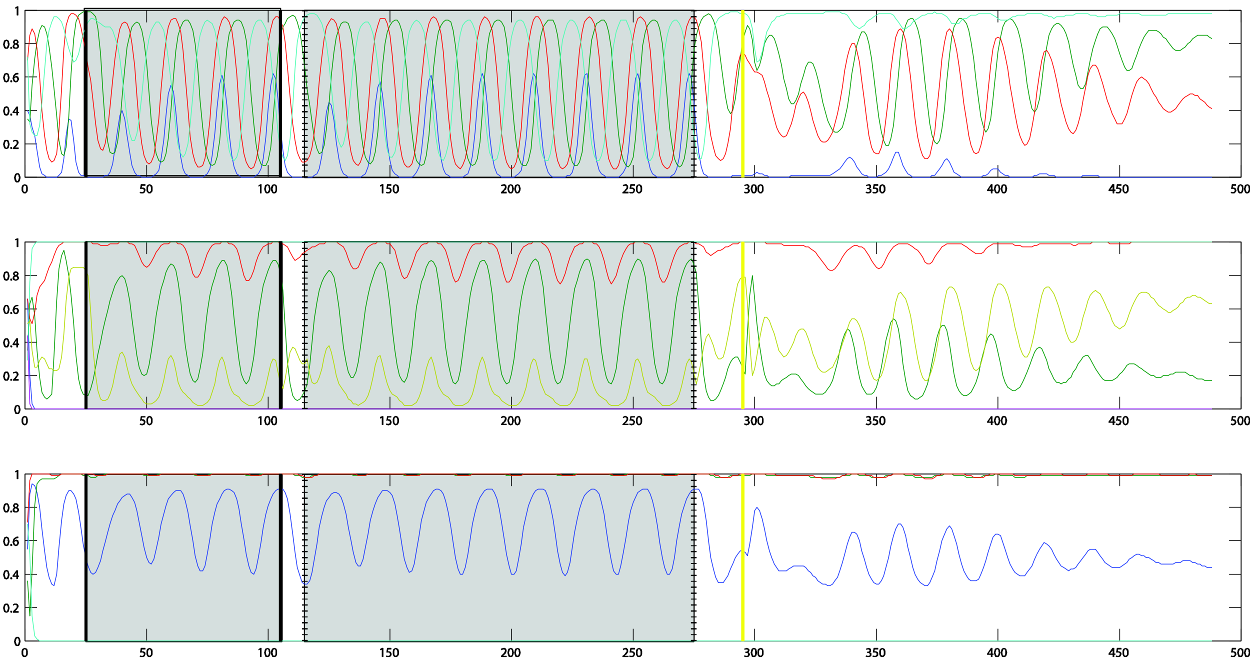


Figure 5. The neural activity in the three layers of the CTRNN during a Duration Comparison task with A=80 and B=160. Each line corresponds to a different layer of the CTRNN.

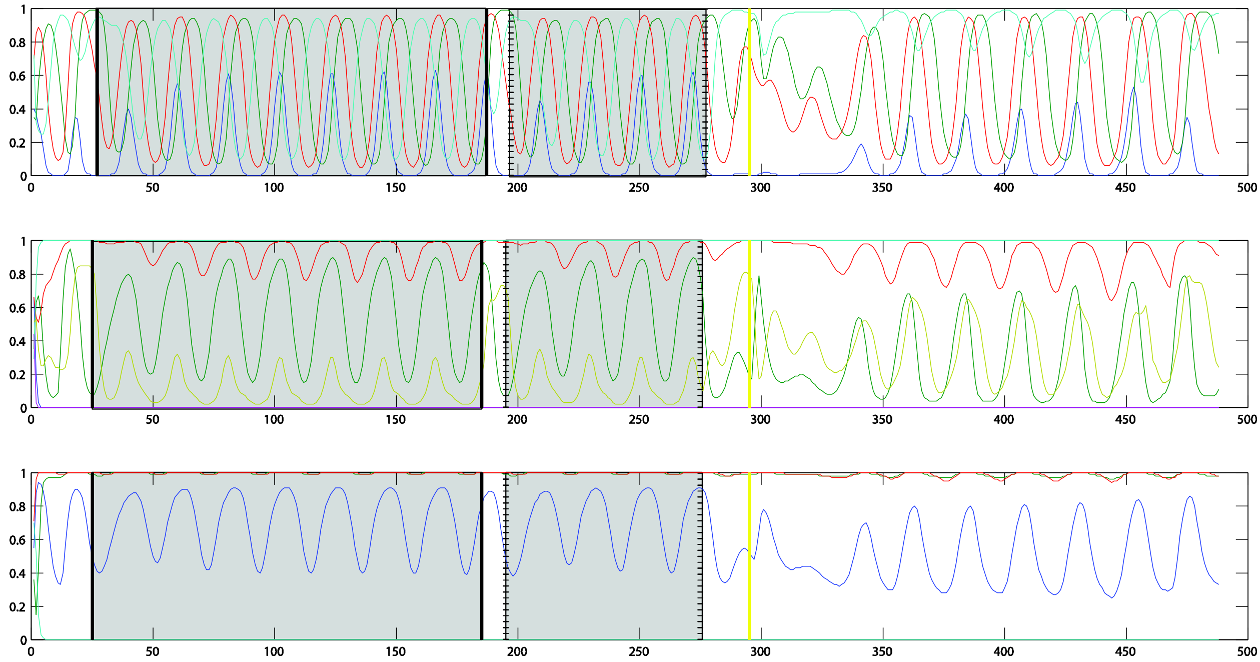


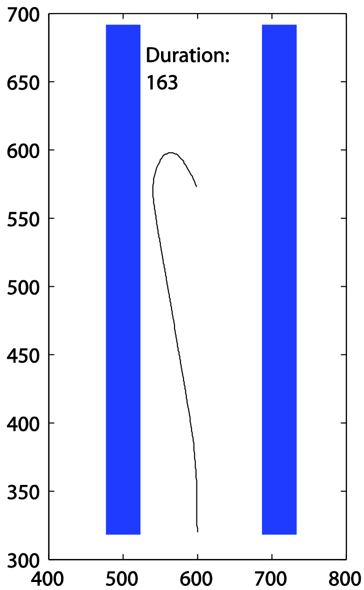
Figure 6. The neural activity in the three layers of the CTRNN during a Duration Comparison task with A=160 and B=80. Each line corresponds to a different layer of the CTRNN.

Besides the fact that the task is clearly separated into two distinct phases of (i) time perception and (ii) robot action, in Figures 5 and 6 we see that the same neurons are activated in the whole duration of the task. In other words there are no neurons devoted only on the perception of time. The neurons supporting ordinary cognitive tasks undertake additionally the responsibility of encoding the flow of time as it is suggested by intrinsic time representations. Moreover, given that the perceived time interval of 160 simulations steps correspond to 16 seconds in the real world, the present results postulate that properly shaped intrinsic time representations can be functional not only for very short but additionally for sufficiently long time intervals.

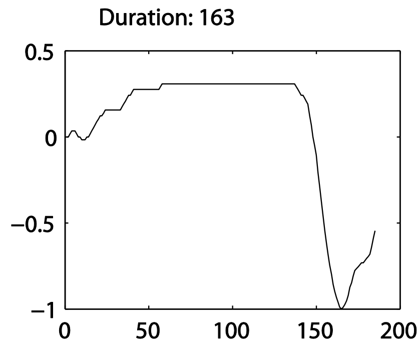
The examination of neural activity in the three network layers shows that there is a slight differentiation of the upper part with respect to time perception. In particular, in some of the upper level neurons, the amplitude of the oscillation increases as long as the agent experiences sound (see for example the activity of the upper level neuron depicted in blue when the agent experiences either interval A or B). This observation complements existing theories of dedicated time representation that assume each oscillation to correspond to a clock tick that is empty of any additional information. According to our results the parameters of the oscillation (in our case, the amplitude) can be actively used for counting and encoding the elapsed time. In other words, oscillations may not operate as passive ticks, but they might be actively involved in time processing.

Duration Reproduction. In this task, the robot has to memorize and reproduce the length of an experienced duration. An indicative performance of the robot when reproducing a temporal interval of 16.3 s (163 simulation steps) is depicted in Figure 7(a). The robot moves forward making a fast 180^{o} turning when the duration reproduction is finished. We examine how robot's motion evolves in time, plotting the sinusoidal of robot's direction in Figure 7(b). The robot moves in a direction that is close to zero (i.e., $(\sin(0^{o}) = 0)$ for a long period but when the end of the reproduction period is approaching it makes a fast turning towards -90^{o} (i.e., $\sin(-90^{o}) = -1)$ that continues making the robot to nearly turn towards 180^{o} (i.e. $(\sin(180^{o}) = 0)$. According to Figure 7(b), the robot memorizes and reproduces time with sufficient accuracy.

We now turn to the internal dynamics of the CTRNN that are shown in Figure 8. The two black vertical lines (start, stop) illustrate the period of continuous time experiencing, while the yellow vertical line illustrates the time that the "go" signal is given to the robot. We can easily see that the oscillatory activity is preserved in all layers of the network. Similar to the previous task, during sound experiencing the upper part of the CTRNN exhibits a counting-like functionality with the amplitude of the oscillation decreasing gradually as time goes by. Interestingly, in the subsequent duration reproduction phase, some neurons show an inverse pattern of activity with the amplitude of the sinusoidal gradually decreasing. This is in fact a reverse counting mechanism that supports accurate duration reproduction. In other words, the agent develops a count up mechanism that is used during duration observation and a count down mechanism that is used during duration reproduction.



(a)



(b)

Figure 7. Part (a) shows the behavior of the agent during the reproduction of a time interval with length 163. The robot moves forward making a sudden turn backwards when it believes that the reproduced period is completed. Part (b) shows the sinusoidal of robot's moving direction (y-axis), during the duration reproduction task. Initially the robot moves at approximately zero degrees ($\sin(0^o) = 0$), and as soon as the reproduction time approaches the end, it turns to -90^o (i.e., $\sin(-90^o) = -1$) and then to 180^o (i.e., $\sin(180^o) = 0$) to face the bottom of the corridor. Overall, the inverse bell curve is centered around 163 simulation steps, which indicates that the robot reproduces the memorized duration with sufficient accuracy.

4. Conclusions

The present work adopts a self-organized computational modeling approach to investigate possible time representations in cognitive systems. Due to the simplicity of the CTRNN model used in our experiments, the present study does not argue to have uncovered the details of time representation in the brain. The time processing capacity of the brain may rely on different and more complex mechanisms and their relation to our findings remain to be experimentally investigated. However, the present work clearly demonstrates that it is possible to integrate the well-known dedicated and intrinsic representations of time into a new biologically plausible representation. To the best of our knowledge this is the first time that such a suggestion appears in the literature. The present work demonstrates that the representations integrating dedicated and intrinsic characteristics can effectively accomplish both Duration Comparison and Duration Reproduction tasks, processing sufficiently long time intervals. Hopefully our study will promote enriching existing theories on the functionality of the brain and thus enable neuroscientists to come up with new and more powerful explanations on interval timing.

According to our results, oscillatory activity plays a fundamental role in the functionality of the overall system. Time is encoded in the active (rather than passive) oscillatory activity of neurons that take care (i) the processing of temporal information and (ii) the interaction of the robot with the environment enabling the accomplishment of tasks. Interestingly, the observed oscillatory pattern incorporates ramp-like characteristics as suggested by neuroimaging studies on interval timing (Leon & Shadlen, 2003; Mita et al., 2009).

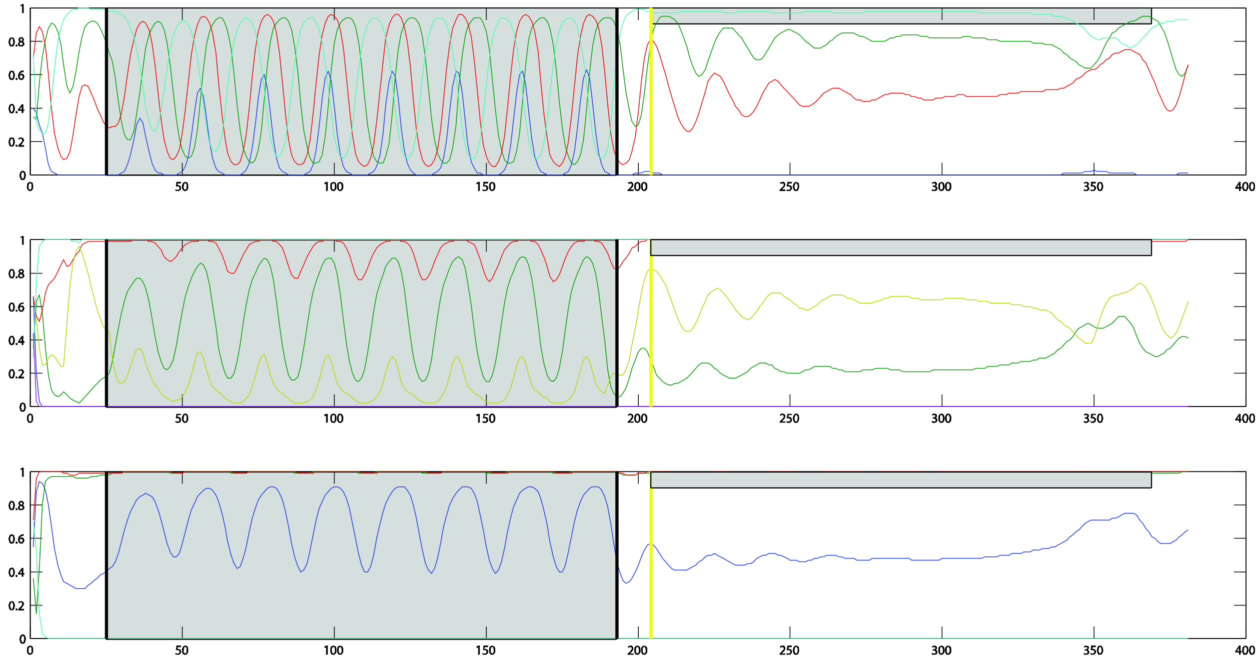


Figure 8. The activity in the three layers of the CTRNN during the Duration Reproduction task for an interval with duration 71. Each line corresponds to a different layer of the CTRNN.

Moreover, our study suggests that time perception may be considered as a higher-level capacity that emerges from monitoring the activities and interactions of other neurons. This is in agreement to the second-order abstracted representation of time proposed in (van Wassenhove, 2009). In our model a counting mechanism is self-organized mainly in the upper part of the CTRNN which in fact receives no direct sensory input, but accomplishes to encode the elapsed time in the amplitude of the oscillatory neural activity. However, key aspects of time perception remain strongly linked with embodiment issues and the control scheme used to direct the motion of the agent (i.e., the oscillatory dynamics guiding the functionality of the whole CTRNN), as it is suggested by (Craig, 2009; Wittmann, 2009).

Interestingly, the perception and processing of time remains particularly unexplored in the field of robotic systems (Maniadakis & Trahanias, 2011) and the present work constitutes an early attempt in this direction. Given the essential role of time in nearly all human 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.

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