

# Integrated Intrinsic and Dedicated Representations of Time: A Computational Study Involving Robotic Agents

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## Abstract

The computational modeling of cognitive processes provides a systematic means to study hidden and particularly complex aspects of brain functionality. Given our rather limited understanding of how the brain deals with the notion of time, the implementation of computational models addressing duration processing can be particularly informative for studying possible time representations in our brain. In the present work we adopt a connectionist modeling approach to study how time experiencing and time processing may be encoded in a simple neural network trained to accomplish time-based robotic tasks. A particularly interesting characteristic of the present study is the implementation of a single computational model to accomplish not only one but three different behavioral tasks that assume diverse manipulation of time intervals. This setup enables a multifaceted exploration of duration-processing mechanisms, revealing a rather plausible hypothesis of how our brain deals with time. The model is implemented through an evolutionary design procedure, making a very limited set of a priori assumptions regarding its internal structure and machinery. Artificial evolution facilitates the unconstrained self-organization of time representation and processing mechanisms in the brain of simulated robotic agents. Careful examination of the artificial brains has shown that the implemented mechanisms incorporate characteristics from both the ‘intrinsic’ time representation scheme and the ‘dedicated’ time representation scheme. Even though these two schemes are widely considered as contradictory, the present study shows that it is possible to effectively integrate them in the same cognitive system. This provides a new view on the possible representation of time in the brain, and paves the way for new and more comprehensive theories to address interval timing.

## Keywords

Time representation, neural network model, artificial time perception, robotic sense of time, evolutionary self-organization, cognitive robotics

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## 1. Introduction

The perception and processing of duration play a key role in many of our daily activities from estimating the remaining time during exams and setting an appointment with friends, to enjoying music and dancing following the rhythm. Understanding how our brain perceives and reasons about time is a challenging issue that attracts rapidly increasing research interest in the neuroscience and cognitive science communities. Contemporary review papers and special journal issues have summarized and are testament to the new and burgeoning scientific findings in the field (Grondin, 2010; Ivry & Schlerf, 2008; Meck, 2005; Wittmann & van Wassenhove, 2009).

Despite the significant research interest that has been devoted to time, the neural underpinnings of the sense of time and the representation of duration in our brain remain rather poorly understood, with controversial theories attempting to explain experimental observations. Broadly speaking, there are two main approaches to describe how our brain represents time (Buetti, 2011; Ivry & Schlerf, 2008). The first is the dedicated approach (also known as extrinsic, or centralized) that assumes an explicit metric of time. This is the oldest and most influential explanation of interval timing. The models included in this category employ mechanisms that are designed specifically to represent duration. Traditionally such models follow an information-processing perspective in which pulses that are emitted regularly by a pacemaker are temporally stored in an accumulator, similar to a clock (Droit-Volet et al., 2007; Gibbon et al., 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 monotonically increasing or decreasing processes to encode elapsed time (Simen et al., 2011; Staddon & Higa, 1999). The second approach includes intrinsic explanations (also known as distributed) that describe time as a general and inherent property of neural dynamics (Dragoi et al., 2003; Karmarkar & Buonomano, 2007). 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. 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 et al., 2008). The SBF model assumes a dedicated timing mechanism in the basal ganglia that is based on monitoring distributed neural activity in the cortex.

The main limitation of the dedicated approach is its weakness in explaining modality-specific differences in time perception. On the other hand, intrinsic models are considered to have limited processing capacity, being inappropriate for exploring time processing in complex and real life tasks. However, both

modeling approaches are supported by neurophysiological and behavioral observations and the debate concerning the representation of time in the brain is now more active than ever.

Interestingly, the mechanisms assumed by the aforementioned models cannot universally process time both in the presence and the absence of continuous external input (e.g., on the basis of start–stop cues). Such a capacity, which is typical for biological cognitive systems, reveals an important lack of existing neurocomputational approaches. To address this issue, abstract clocklike mechanisms have been typically employed (Jazayeri & Shadlen, 2010; Taatgen et al., 2007). The present study aims to shed light on possible neurocomputational mechanisms that can effectively perceive time both in the presence and the absence of external stimuli.

Besides the human devised representations of time that have been discussed above, the time-processing mechanisms of our brain may exhibit different characteristics compared to the ones considered so far. Self-organized computational modeling can serve as a new tool that facilitates the exploration of alternative representations (Ruppin, 2002), and thus facilitates convergence in the time representation debate. This is the aim of the present study, which employs a simulated robotic setup to investigate possible neurocomputational representations of duration. The obtained results provide a fresh and unconventional view on the possible time-processing mechanisms of the brain, and may provide inspiration for future work in this field.

In contrast to the majority of existing time representation models, which start with a key assumption of following either the dedicated or the intrinsic approach and then hand code the details of the model, the present work does not make any a priori assumption but employs an automated design procedure to explore and propose efficient representations of time. To this end, the present study considers three different time-processing tasks, namely Duration Comparison, Duration Reproduction and Past Characterization that have to be accomplished by the very same robotic cognitive system. The ‘behavioral’ approach adopted in the current paper links with the Behavioral Theory of Timing (Killeen & Fetterman, 1988) and Learning to Time (Machado, 1997). These theories assume that the behavioral vocabulary of subjects supports duration perception, a view that has also been supported by recent experimental work (Gouvea et al., 2014).

We employ a Continuous Time Recurrent Neural Network (CTRNN) (Beer, 1995; Maniatakis et al., 2009a) to develop an ‘artificial brain’ for the robotic agent. An evolutionary design procedure based on Genetic Algorithms (Nolfi & Floreano, 2000) is used to search possible configurations of the artificial brain that can accomplish the three aforementioned tasks. This procedure promotes the unbiased self-organization of time representation in the cognitive system. The functional responsibilities endowed to the cognitive system as a

consequence of the robotic experimental setup, and the probabilistic optimization of CTRNN configurations as a result of the evolutionary exploration, do not only address what is possible in terms of time representation but, even more importantly, which are the more likely characteristics of such a representation.

Following a series of statistically independent experiments we obtain a set of artificial brains that fit the behavioral requirements of our study (i.e., accomplish the three duration-processing tasks). The automatically designed artificial brains are subsequently studied to reveal the characteristics of effective time perception mechanisms that may also be valid for interval processing in the brain. The obtained results show that a very effective modeling approach may result from combining the key characteristics of the dedicated and intrinsic time representations. In short, the neural circuits that support ordinary cognitive processing operate in an oscillatory mode that enables the encoding of elapsed time in the amplitude of the oscillation. This new representation facilitates the multimodal processing of time intervals as indicated by the accomplishment of the three different duration-processing tasks.

Interestingly, the perception and processing of time is particularly new in the field of robotic systems (Maniadakis & Trahanias, 2011). Work in the emerging research branch of robotic time perception is expected to significantly contribute to the seamless integration of artificial agents in human societies.

The remainder of the paper is structured as follows. The next section summarizes the experimental setup, describing (i) the simulated robot and the artificial brain used to endow it with cognitive and behavioral capacities, (ii) the behavioral tasks considered in the present work, and (iii) the evolutionary procedure employed to explore effective CTRNN configurations. In the following section we describe the obtained results, focusing on the internal mechanisms of the artificial brains. Then we discuss how our findings compare to the dedicated and intrinsic representations of time. In the last section we summarize the characteristics of the new time representation suggested by our experiments and we provide directions for future work.

## **2. Materials and Methods**

The present work puts forward a new framework for the study of time perception that is based on robotic cognitive systems. The underlying computational approach exhibits unique characteristics in terms of exploring possible representations and mechanisms of interval timing, which account for:

- the placement of the robot in a specific environment where in addition to the processing of time it has to consider behavior planning and the interaction with objects;
- the uninterrupted sensory-motor flow and the continuous processing mode of the robotic cognitive system;
- the behavioral, as opposed to the symbolic expression of the robot's decision, in the form of a sequence of motor commands.

## 2.1. Experimental Setup

### 2.1.1. Simulation Environment

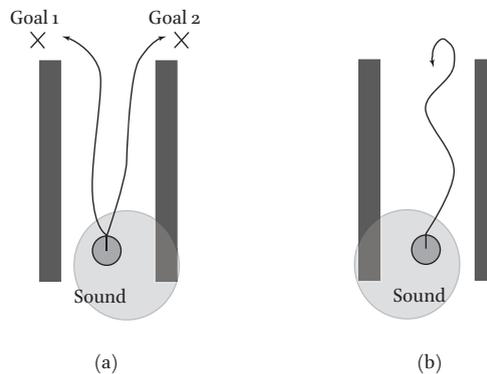
We have implemented a simulation of a two-wheeled mobile robot equipped with eight uniformly distributed distance, light and sound sensors. The distance sensor is mainly used during navigation to avoid the robot bumping into the walls. The light sensor is used to receive a task indicator informing the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

The simulated robot operates in a rather simple environment with two walls located on its left and right side (Fig. 1). The robot has to perceive the duration of sound cues and drive without bumps along the corridor that is formed 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.

The selected time step is sufficiently small to support the interaction of the robot with the environment and additionally it is sufficiently large to reduce the computational resources required to design an artificial brain to the order of approximately one day (when running on a single computer). Similar time steps are typical for robotic simulation experiments, and have been used extensively in our previous studies on time perception (Maniadakis & Trahanias, 2012; Maniadakis et al., 2009a, 2009b, 2011). Interestingly, the duration of 100 ms is frequently assumed to correspond to the resolution of cognitive steps in our brain (Dehaene & Naccache, 2001; van de Par & Kohlrausch, 2000).

### 2.1.2. The Brain of the Robot

A three-level Continuous Time Recurrent Neural Network (CTRNN) (Beer, 1995; Maniadakis & Tani, 2008) is used to provide the artificial agent with behavioral and cognitive capacities. This type of network represents knowledge in terms of internal neurodynamic attractors and it is therefore particularly appropriate for implementing cognitive capacity that is inherently continuous, similar to our mind.



**Figure 1.** A graphical representation of the experimental setup. The robot is depicted as a small circle at the beginning 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° turn as shown in part (b).

The network consists of four neurons in the upper level, six neurons in the middle level and four neurons in the lower level. Full intra- and interlevel connectivity is assumed in the model. Synaptic weights are determined by an evolutionary procedure (described below) and they remain constant during task testing. Similar to previous studies (Paine & Tani, 2005; Yamauchi & Beer, 1996) CTRNN neurons are governed by the standard leaky integrator equation:

$$\frac{d\gamma_i}{dt} = \frac{1}{\tau} \left( -\gamma_i + \sum_{k=1}^R w_{ik}^s I_k + \sum_{m=1}^N w_{im}^p A_m \right) \quad (1)$$

where  $\gamma_i$  is the state (cell potential) of the  $i$ -th neuron. All neurons in a network share the same time constant  $\tau = 0.25$  in order to avoid explicit differentiation in the functionality of CTRNN parts. This time constant is a key parameter for the functionality of the model, because it synchronizes the processing mechanisms of the network with the rate of sensory-motor information flow.

The state of each neuron is updated according to external sensory input  $I$  weighted by  $w^s$ , and the activity of presynaptic neurons  $A$  weighted by  $w^p$ . After estimating the neural state by eqn. (1), the activation of the  $i$ -th neuron is calculated by the non-linear sigmoid function according to:

$$A_i = \frac{1}{1 + e^{-(\gamma_i - \theta_i)}} \quad (2)$$

where  $\theta_i$  is the activation bias applied on the  $i$ -th neuron.

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. The four neurons at the lower level of the CTRNN are connected to a motor neuron that controls the wheels of the robot. The speed for each of the two wheels is determined by a pair of neurons operating according to the flexor/extensor principle (i.e., one increases and the other decreases the speed of the wheel). Let us assume that at a given time step, the activation of the motor neuron is  $A_m$ . Then, the left and right wheel speed of the simulated robot is given by:

$$speed_l = 0.4 + 0.6A_m \quad speed_r = 0.4 + 0.6(1 - A_m) \quad (3)$$

Following this approach the agent moves with a constant total speed, while the activation  $A_m$  controls the direction of movement.

## 2.2. Behavioral Tasks

To explore time representations through artificial neural network self-organization, the present study considers simple maze tasks that have to be achieved by a simulated robotic agent, similar to Blynel and Floreano (2003), Maniadakis and Trahanias (2006), and Ziemke and Thieme (2002). Each one of the three tasks addresses a different aspect of duration processing. More specifically, there are two main types of experiments in the field of interval timing memorization, one focusing on duration comparison and the other on the reproduction of an earlier presented duration (Taatgen & van Rijn, 2011). In the present study we explore both of these types, considering additionally a simplified example of past time stamping. The three tasks explored in the present work are described in detail below.

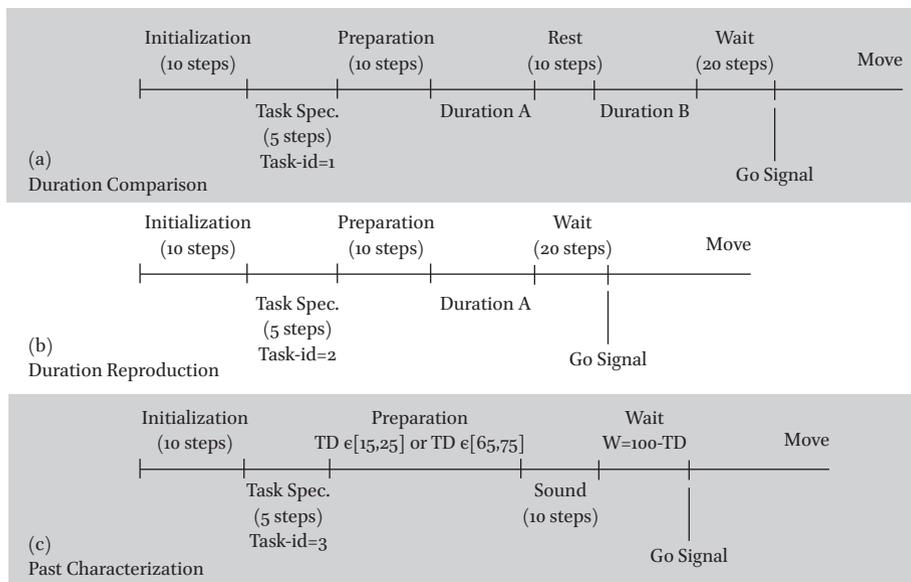
### 2.2.1. Duration Comparison

The experiment 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 Fig. 1a).

The experiment 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 Fig. 2a). 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 ten 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 that are used as goal positions for the robot, as shown in Fig. 1a. Depending on whether  $A$  was 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 approximately reach Goal1, but when  $A > B$  the agent should approximately reach Goal2). Additionally, during navigation, we consider the number *Bumps* of robot bumps into the walls. Overall, the success of the agent to a given duration comparison  $i \in \{A > B, A < B\}$  is estimated as:

$$S_i = \frac{100}{D(\text{Bumps} + 1)} \quad (4)$$



**Figure 2.** The structure of (a) the Duration Comparison, (b) the Duration Reproduction, and (c) the Past Characterization experiments.

By maximizing  $S_{A>B}$  and  $S_{A<B}$  we aim at minimizing the distance from the goals, therefore producing responses at the correct side of the corridor as well as avoiding bumping into 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:

$$FIT_{DC} = S_{A>B} \cdot S_{A<B} \quad (5)$$

### 2.3. 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. To demonstrate the end of the reproduction period, the robot makes a quick  $180^\circ$  turn as shown in Fig. 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 Fig. 2b). Subsequently, the agent experiences a sound with temporal duration  $A$ , which 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  $A$ . As soon as the robot believes that the  $A$  interval has been completed, it immediately has to make a  $180^\circ$  turn, and continue navigation facing the beginning of the corridor.

To evaluate the response of the artificial agent we consider its direction of motion in the whole period of duration reproduction. To enable the robot to express the  $180^\circ$  turn in a sequence of actions, we examine the robot's behavior for  $A + 30$  simulation steps (i.e., a period slightly longer than  $A$ ).

During the reproduction of the  $A$  interval, the robot must move mostly forward, which means its direction  $Dir$  should be approximately  $0^\circ$ . Just after the completion of  $A$  and for the next 30 steps, the robot must turn in the opposite direction, steering at  $180^\circ$ . The success of the agent in the duration reproduction task is numerically evaluated by:

$$FIT_{DR} = \frac{1}{\sum_1^{length(A)} Dir^2 + \sum_{length(A)+1}^{length(A)+30} (180 - Dir)^2} \quad (6)$$

By maximizing  $FIT_{DR}$ , we aim at minimizing the difference between the direction in which the robot moves and the optimal moving direction as explained above.

### 2.4. Past Characterization

The procedure assumes that the robot experiences a sound and after some time it is asked to judge whether this particular experience was a short or a long time ago. The robot responds by navigating along the corridor and turning either to the left side in the case that the sound event happened in the distant past, or to the right side in the case that the sound appeared in the recent past (see Fig. 1a).

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. 2c). Subsequently, a preparation interval follows with duration  $TD$  randomly specified either in the range  $TD \in [15, 25]$  (for the case of distant past), or  $TD \in [65, 75]$  (for the case of recent past). After a sound is

emitted, a waiting period follows that is dynamically specified as  $W = 100 - TD$ . As a result, the pair of durations  $TD$  and  $W$  determines whether the sound experience of the agent was a long or a short time ago.

At the end of the waiting period the agent is provided a 'go' signal and it starts navigating towards the end of the corridor. To evaluate the response of the robot we use the two goal positions that were also employed in the Duration Comparison experiment (see Fig. 1a). Depending on whether the sound was actually experienced by the agent in the distant or the recent past, we select the appropriate goal position and we measure the minimum distance  $D$  of the agent's path from that goal (i.e., in the case of distant past the agent should steer towards Goal1, while in the case of recent past the agent should steer towards Goal2). To evaluate the robot's response we use two success measures  $S_{\text{distant}}$  and  $S_{\text{recent}}$  defined according to eqn. (4). Overall, the capacity of the robot to accomplish the Past Characterization task is estimated as:

$$FIT_{\text{PC}} = S_{\text{distant}} \cdot S_{\text{recent}} \quad (7)$$

## 2.5. Evolutionary Design

We employ a Genetic Algorithm (GA) to explore possible cognitive mechanisms that enable the artificial agent to perceive and process time in accomplishing the three behavioral tasks described above (Nolfi & Floreano, 2000). This approach is based on using optimization procedures to train agents in accomplishing tasks. Readers not familiar with evolutionary optimization may simply omit the rest of this section, considering this part of the work as a black box procedure that accomplishes parametrical tuning of the CTRNN.

GAs accomplish an abstracted simulation of biological evolution by producing a sequence of robot generations that are gradually fitted to the design criteria specified. In the current work, these criteria consist in the successful accomplishment of the three duration-processing tasks. We use a population of 1000 artificial chromosomes, each one encoding a different CTRNN configuration, or a different robot brain. Each candidate CTRNN solution is tested on a randomly initialized version of the three tasks. To get an estimate of the CTRNN's time-processing capacity, we combine in a multiplicative manner the performance metrics associated with each one of the three tasks. Therefore, the global fitness of a chromosome is defined as follows:

$$F = FIT_{\text{DC}} \cdot FIT_{\text{DR}} \cdot FIT_{\text{PC}} \quad (8)$$

This is the fitness function that drives the exploration of CTRNN configurations. By maximizing  $F$ , we get robot brains that can satisfactorily accomplish the three duration-processing tasks considered in the present study.

We have used a standard GA process with survival of the fittest individuals along consecutive generations (Nolfi & Floreano, 2000). Real-value encoding is used to map synaptic weights and neural biases of the CTRNN into chromosomes. 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 in the chromosome, with each CTRNN parameter having a probability of 4% to be mutated. Mutation facilitates the exploration of new, gradually more effective solutions that will be transferred to the next generation (through crossover).

In all evolutionary runs the randomly initialized population is evolved for a predefined number of 500 generations. The present work focuses on temporal cognition mechanisms, rather than the robotic behaviors, which means that robot responses should be mainly considered as proofs of the

time-processing capacity of the cognitive system. In some of the obtained results the details of the robotic behaviors could improve further by using a very long evolutionary procedure. However, optimal robotic behaviors would probably be a result of overfitting. This is rather inappropriate for the present study that wants to explore the qualitative characteristics of time-processing capacities in artificial cognitive systems. The evolutionary procedure was therefore interrupted after the predefined number of 500 generations, which proved adequate for the successful evolution of time-processing skills.

### **3. Results**

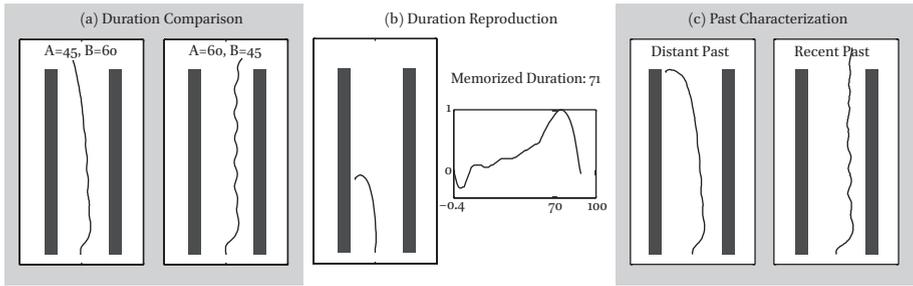
We have conducted ten statistically independent evolutionary runs to explore possible neural mechanisms that are capable of accomplishing the three duration-processing tasks described above. The evolutionary procedures converged successfully in six of the runs, producing artificial brains that are able to perceive and process time. The remaining four ineffective artificial brains were excluded from our study. Theoretically speaking, it is possible to increase the success rate of the evolutionary procedure by adjusting mutation and crossover operators. However, our focus is on time-processing mechanisms and since the details of artificial evolution do not affect the machinery of CTRNN solutions, it is outside the scope of the present study to identify the mutation and crossover rates that result in the most effective evolutionary scheme.

In order to obtain insight into the mechanisms self-organized in the robot brains, we have investigated neural activity in the successfully evolved CTRNN configurations. Interestingly, even if the evolutionary procedures were statistically independent, all obtained results show (qualitatively) similar internal mechanisms. Below we discuss the characteristics that are common between successful artificial brains, using as a working example one representative of the CTRNN configurations.

It is necessary to note here that the evolutionary procedure is searching for CTRNN mechanisms capable to successfully accomplish the three duration-processing tasks discussed above, but there is no explicit request for implementing duration-processing mechanisms. However, as is discussed below, the functionality of the CTRNN relies on a fully emergent mechanism that resembles duration counting.

#### *3.1. Duration Comparison*

To assess the duration comparison capacity of the model, we have tested multiple pairs of random durations. In all cases the robot could robustly perceive the duration of intervals, compare their lengths, and finally respond successfully by driving to the end of the corridor and turn towards the side that corresponds to the longest interval. The behavior of the robotic agent when comparing two time intervals with durations of 45 and 60 simulation steps is shown in Fig. 3a. The robot, rather than navigating in the middle of the free corridor space and then

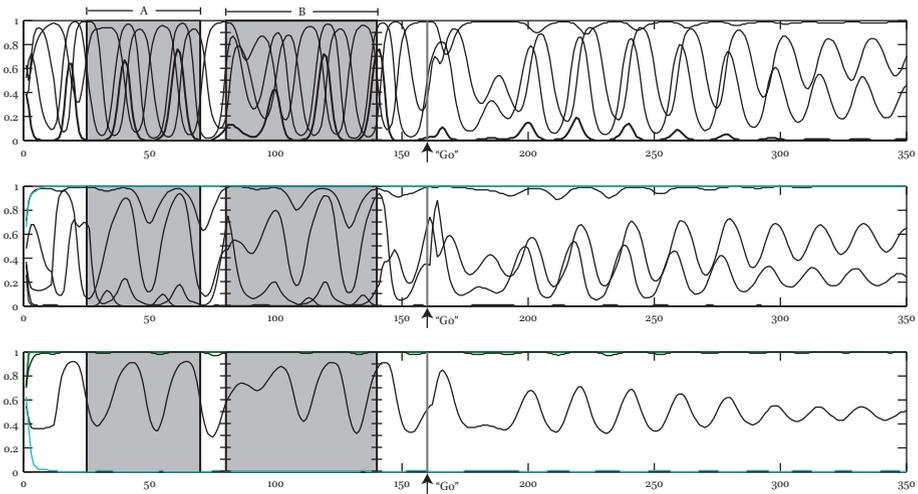


**Figure 3.** The behavioral responses of the robot in the three tasks considered in the present study. (a) Duration Comparison. In the first case the robot compares intervals A and B with durations of 45 and 60 simulation steps respectively. In the second case the robot compares intervals A and B with durations of 45 and 60 simulation steps. (b) Duration Reproduction. The first plot shows the behavior of the agent during the reproduction of a time interval with length 71. The robot moves forward, making a sudden turn backwards when it believes that the reproduced period is completed. The second plot shows the sinusoidal of the robot's moving direction ( $y$ -axis), during the duration reproduction task. Initially the robot moves at approximately zero degrees ( $\sin[0] = 0$ ), and as soon as the reproduction time approaches the end it turns to  $90^\circ$  (i.e.,  $\sin[90] = 1$ ) and then to  $180^\circ$  (i.e.,  $\sin[180] = 0$ ) to face the beginning of the corridor. The bell curve is centered at 74 simulation steps, which indicates that the robot reproduces the memorized duration with sufficient accuracy. (c) Past Characterization task. The two plots show that the robot responds correctly to the experience of sound either in the distant or recent past.

turning either left or right, adopts a motion strategy that distinguishes between the two options very early. This is because our model does not assume an explicit working memory module that temporally stores comparison results to be used when the robot approaches the end of the corridor. Alternatively, in our model, the dynamics of neural activity encode the result of the comparison, which slightly but constantly affects the motion plan, gradually moving the robot to the chosen side.

The neural activities in the three layers of the CTRNN when the robot compares two time intervals with lengths  $A = 45$  and  $B = 60$ , are shown in Fig. 4. Each subplot corresponds to a different layer 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 fifth vertical 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 mainly governed by oscillatory dynamics. The phase of the oscillation is largely determined by the time constant  $\tau$  used in the equation of the leaky integrator neuron model and the simulation step used in our experiments. The synchronization of this particular triplet (phase, time constant, simulation step) is critical for the functionality of the model. Changes in any of these three parameters may destroy the functionality of the cognitive system in the given experimental setup.



**Figure 4.** The neural activity in the three layers of the CTRNN during a Duration Comparison task with  $A = 45$  and  $B = 60$ . Each plot corresponds to a different layer of the CTRNN.

Oscillations are particularly useful from a time representation perspective, because they provide a means for measuring time intervals (i.e., by counting the number of oscillations) as is suggested by dedicated timing representations (Gibbon et al., 1984; Large, 2008). At the same time, from a robot control perspective, 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-processing tasks. This is in support of the theories promoting a strong correlation between embodiment and time perception (Craig, 2009; Gouvea et al., 2014; Wittmann, 2009).

Besides the fact that the task is clearly separated into two distinct phases of (i) perception and (ii) action, in Fig. 4 we see that the same neurons are activated for the whole duration of the task. In other words, there are no neurons devoted only to time perception. The neurons supporting ordinary cognitive tasks undertake additionally the responsibility of encoding the flow of time as is suggested by intrinsic time representations. Moreover, given that 100 simulation steps in our study correspond to 10 s in the real world, the present results postulate that intrinsic time representations can be functional not only for very short but additionally for sufficiently long time intervals (Maniadakis et al., 2014).

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 with a thick line, when the agent experiences

either interval *A* or *B*, in Fig. 4). This suggests that duration may be encoded in the amplitude of the oscillatory activity. The latter observation complements pacemaker–accumulator models that assume each oscillation to correspond to one temporal unit, or one clock tick (Gibbon et al., 1984). 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 only operate as passive ticks, but they might be actively involved in the processing of time.

However, apart from interval timing, the increasing amplitude may also encode the probability for a left- or right-directed robot response. Unfortunately, there is no easy way to distinguish whether the increasing amplitude corresponds to either duration perception, or decision making, or both, similar to the problem of explaining the ramplike activity that has been observed in several brain areas (Matell & Meck, 2004). Our intuition from experimenting with the model is that the higher-level activity measures time, in support of the decision-making procedure similar to results by van Rijn et al. (2011), and thus duration perception and decision making coexist in the model.

### 3.2. Duration Reproduction

In this task, the robot has to memorize and reproduce the length of an experienced duration. The trace of the robot when reproducing a temporal interval of 71 simulation steps is depicted in the first plot of Fig. 3b. To assess the accuracy of duration reproduction we examine how the direction of robot's motion evolves over time. The second plot of Fig. 3b shows the sinusoidal of the direction of the robot during task execution. The sinusoidal of the direction is close to zero during the first 60 steps of the robot's motion, indicating that the robot moves approximately at  $0^\circ$  (i.e.,  $\sin[0] = 0$ ). When 60 steps have passed, the robot registers that the reproduction period is about to finish and it starts turning. This is indicated by the gradual increase of the sinusoidal of the robot's direction (i.e.,  $\sin[90] = 1$ ), which soon after that drops again to approximately zero (i.e.,  $\sin[180] = 0$ ). According to the second plot of Fig. 3b, the robot's turn is centered on 74, indicating that the robot has approximately memorized and reproduced the original time interval of length 71.

We now turn to the internal dynamics in the upper layer of the CTRNN (neural activity in the middle and lower layer also follow oscillatory patterns, but in the discussion we concentrate on the upper layer of the network, which exhibits more time-relevant activity). The two black vertical lines shown in Fig. 5a delineate the period of time experiencing, while the third vertical line corresponds to the time that the 'go' signal is given. During sound perception the upper part of the CTRNN exhibits a counting-like functionality with the amplitude of the oscillation increasing gradually as time goes by (see neural activity depicted with thick lines). Interestingly, in the subsequent duration reproduction

phase, one of the thick-drawn neurons shows an inverse pattern of neural activity with the amplitude of the sinusoidal gradually decreasing, similar to a reverse counting procedure.

Based on these observations, it seems that the artificial agent develops a count-up mechanism that is used for duration observation and a count-down mechanism that is used for duration reproduction. Actually, this constitutes a novel explanation that is rarely considered in the literature. Note that a full reset of interval counting at the end of the sound-experiencing phase (Spencer et al., 2009), would render the count-down mechanism inappropriate for the given task. In such a case, more resources might be required by the cognitive system in order to explicitly memorize the experienced duration and repetitively compare the memorized duration with the currently reproduced duration.

The Duration Reproduction task provides the means to explore whether the observed mechanisms exhibit the scalar characteristics that are typically observed in biological timing mechanisms (Lejeune & Wearden, 2006). Scalar timing implies that (i) measurements should vary linearly and near-accurately as time increases and (ii) the variance of the perceptual mechanism increases as the duration of time also increases. We test the performance of the CTRNN in three sets of ten randomly initialized Duration Reproduction trials (i.e., each trial is performed with different additive noise on the sensors supporting robot–environment interaction). The first set concerns intervals of 37 simulation steps, the second concerns intervals of 50 simulation steps and the last, intervals of 85 simulation steps. Since the robot does not provide an instant response but specifies the end of the reproduction interval with a sequence of actions resulting in a turn of  $180^\circ$ , we have used the simulation step with a maximal change in the robot’s direction as the indicator of the end of reproduction. Table 1 summarizes the success rate of the robot in reproducing the aforementioned intervals. The mean and the variance of the robot’s estimates of the observed intervals are shown in the last two columns of the table. The average of the estimated intervals remains close to the true time in all three cases, satisfying mean accuracy, and the variance increases as the robot experiences longer intervals. These observations indicate that CTRNN timing largely complies with the scalar property.

However, the self-organized mechanisms also exhibit some limitations. More specifically, the average time estimates shown in Table 1 are constantly shifted to the right compared to the true time value. This might be due to the simplified approach we have used to select the point indicating the end of reproduction. Additionally, the scalar property assumes a constant *coefficient of variation*. However, this is not true for our model, indicating a direction for future advancements. Nevertheless, it is worth emphasizing that the two main characteristics of the scalar property (i.e., mean accuracy and scalar variance) have been self-organized without any explicit instructions by the modeler. We

**Table 1.**

The performance of the simulated robot in the three sets of randomly initialized Duration Reproduction trials

True time	Reproduced time in 10 random trials										Mean	Variance
	1	2	3	4	5	6	7	8	9	10		
37	41	42	44	45	44	44	42	44	42	43	43.1	1.49
50	51	55	55	55	55	52	51	52	56	52	53.4	3.44
85	88	88	93	90	87	88	87	87	92	91	89.1	4.4

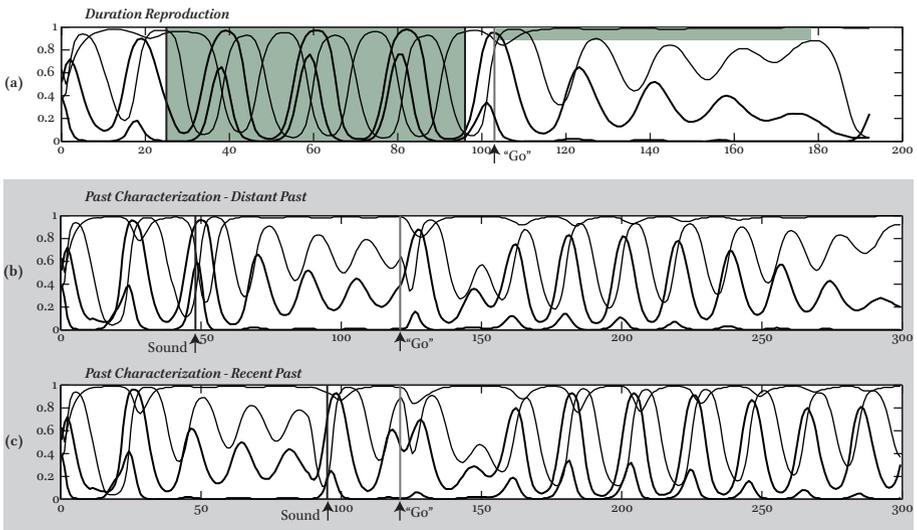
assume that a constant coefficient of variation may easily emerge when constraints relevant to the scalar property are introduced in the evolutionary design procedure.

### 3.3. Past Characterization

In this task, the robot has to characterize the temporal distance of a given sound cue, choosing whether the sensory experience was a long or a short time ago. The robot expresses its belief by navigating to the end of the corridor and then turning either to the left or the right side (left corresponds to distant past, while right corresponds to recent past). The behavior of the robot for each of the two cases is shown in Fig. 3c. In the first case, the robot experiences a sound 70 steps prior to the go signal, while in the second case the robot experiences a sound 27 steps prior to the go signal.

The activity in the upper level of CTRNN neurons for each of the two cases is shown in the two plots of Figs 5b and c. The onset of sound is indicated by the first vertical line. The second vertical line shows the time that the 'go' signal is given. Examining the internal activities of the CTRNN, we observe that the sound triggers a mechanism that resembles countdown as observed in the Duration Reproduction task. More specifically, in the distant past condition the amplitude of the sinusoidal increases with the emission of sound (see thick lines in the first plot of Fig. 5b). This increase is followed by reverse counting that continues until the amplitude has a sufficiently low value, indicating that it was a long time ago since a sound was experienced. In the recent past condition (see the plot of Fig. 5c) the amplitude of the sinusoidal increases again with the emission of sound, but now there is not enough time for the amplitude to decrease and thus the robot can easily understand that it has been a rather short time since the last presence of the sound.

Overall, by considering the level of decrease in the amplitude of the oscillation, the robot distinguishes between sound observation in the distant or recent past, and implements diverse behavioral responses for the two cases of past characterization (see Fig. 3c). In other words, the amplitude of the oscillatory neural activity can not only operate as a possible accumulator, but may also



**Figure 5.** The activity in the upper layer of the CTRNN in (a) the Duration Reproduction task where the length of the perceived and reproduced interval is depicted with a gray box, (b) the Past Characterization task for the case of time experiencing in the distant past, and (c) the Past Characterization task for the case of time experiencing in the recent past.

integrate an inverse counting capacity, therefore being actively engaged in decision making.

### 3.4. Summary

To develop a global view of the functionality of the model, we outline the mechanisms enabling the processing of time. First, it is necessary to note that cognitive activity in the CTRNN is guided by properly shaped neurodynamic attractors encoding the current state of the network (Beer, 1995). A neurodynamic mechanism related to the quantitative properties of time is likely to exist in the upper level of the network where cognitive dynamics follow an attractor of increasing size that is correlated with the duration of the time elapsed. The increasing size of the attractor during time perception is the dynamic analogy of a discrete accumulator that counts clocklike tics. In the Duration Comparison task, depending on the relative size of the attractors during the perception of  $A$  and  $B$  intervals, the cognitive system decides to follow either the left-directed motion path, or the right-directed motion path, implemented by separate behavioral attractors. In the case of the Duration Reproduction task, the increasing perceptual attractor in the upper level of the CTRNN encodes the duration of the presented interval, which is then used as a starting point of the counting-down procedure that enables accurate reproduction. When the amplitude of the oscillation is close to zero, the agent makes a

fast turn towards the beginning of the corridor to indicate the end of the interval. Finally, in the Past Characterization task, the counting-down procedure implemented as a gradually decreasing oscillation amplitude is employed to measure the distance to the past. In the case that the event has occurred in the distant past, the amplitude decreases to approximately zero and the robot initiates the left-directed path. When the perceived event occurred in the recent past, there is not enough time for the amplitude to decrease and the robot follows the right-directed motion path.

Oscillations guide neural activity in all three layers of the CTRNN facilitating the integration of top-down and bottom-up effects on robot cognition. The top-down effect regards the processing of time and the transformation of time judgments to motion commands. The bottom-up effect regards the abstraction of a numerical notion of time out of the lower-level oscillations as well as the modulation of motion planning by interaction with the environment. Even if different roles are assumed for the three layers of the CTRNN, their performance is not isolated and they remain strongly and bidirectionally linked on the basis of oscillatory activity. In other words, what is functional is the composite CTRNN model rather than the isolated layers of neurons. Capitalizing on the sense of the flow of time provided by these oscillations, the robot implements a counting-like mechanism that facilitates the accomplishment of the given duration-processing tasks. Moreover, in contrast to the behavioral approaches such as the Behavioral Theory of Timing (Killeen & Fetterman, 1988) and the Learning to Time (Machado, 1997), we have not observed the formulation of any type of adjunctive or sub-behaviors that facilitate interval timing.

To explore the generalization of the CTRNN mechanisms and their applicability in processing intervals in the order of a few tenths of seconds, we have run supplementary simulation experiments with the robot considering durations of up to 200 simulation steps (these correspond to 20 s in the real world, as indicated by the simulation step of 100 ms used in our study). The new group of experiments showed that by using the CTRNN mechanisms described above, the robot can successfully accomplish the three tasks, effectively processing the extended durations.

Focusing on duration processing and according to the observed neurodynamics, the passage of time is intrinsically encoded in the ordinary activity of neurons that takes care of the behavioral accomplishment of tasks. However, pure oscillatory activity is not enough for the composite system to be aware of interval duration. A higher-level process is necessary to monitor lower-level activity and extract quantitative measurements encoded in the amplitude of the oscillation. Interestingly, the implemented counting-up and counting-down mechanism is appropriate to process time both in the presence and the absence of external sensory input. The latter constitutes a unique feature of our work, which differentiates the present CTRNN model from previous

neurocomputational models. The interval timing mechanism that emerges from our model is in agreement with the proposal for a higher level representation of duration (van Wassenhove, 2009).

#### **4. Discussion and Conclusions**

The present work adopts a computational modeling approach to investigate time representation in cognitive systems. Undoubtedly, the complexity of the CTRNN model used in our study can hardly compare to the complexity of the brain and we therefore do not argue to have uncovered all details of time processing in the brain. In contrast, the aim of the present work has been to explore possible representations of time, focusing on the qualitative characteristics of emergent (rather than pre-constrained) representations in computational cognitive systems. Such an approach is particularly useful to propose alternative but feasible and biologically plausible explanations on interval timing, whose validity remains to be experimentally studied in the brain. In other words, even if the present study does not aim to introduce ‘The Model’ of interval timing, many characteristics of the observed timing mechanisms may be established as valid brain features. These may regard the perception of duration by the higher levels of the cognitive system, the combination of the oscillatory activity with amplitude adaptations, the probabilistic information that may be encoded in the amplitude, and the role of counting and inverse counting mechanisms when dealing with duration-processing tasks. The present computational study may be a significant source of inspiration for enriching existing theories on the functionality of the brain and thus enable neuroscientists to come up with new and more powerful explanations.

The experimental approach followed in the present study accomplishes an unbiased exploration of possible time representations by considering (i) the functional integration of time processing with other skills, in the framework of time-dependent robotic behavioral tasks, (ii) the embodied exploration of duration-processing capacity in dynamic and noisy experimental setups that improve the generalization of the computational model, and (iii) the ability of the ‘very same model’ to address not only one, but three different duration-processing tasks.

Interestingly, the results obtained in the present study demonstrate that it is possible to integrate the dedicated and intrinsic models of time into a new enhanced modeling approach with more explanatory power. More specifically, our robotic experiments suggest that:

- Interval timing can be encoded in the activity of neurons supporting ordinary cognitive tasks. This is the main idea behind intrinsic time representation. So far, the main argumentation against intrinsic approaches (Karmarkar & Buonomano, 2007) has been that they can only be useful for the processing

of short duration intervals and thus they have rather little to offer in the processing of longer durations which are typically considered in human daily activities (even if the processing of long durations should not necessarily assume oscillatory activity — e.g., Staddon & Higa, 1999). Our study has clearly shown that, by exploiting oscillatory dynamics, it is possible to encode time in the activity of neurons that support other cognitive capacities and this approach can effectively be used for the processing of relatively long temporal durations, facilitating the accomplishment of complex behavioral tasks.

- Counting oscillations can effectively facilitate the estimation of the elapsed time as suggested by dedicated representation models (Gibbon et al., 1984; Large, 2008). However, our model shows that duration can be encoded in the parameters of the oscillatory activity (in the amplitude of the oscillation in the case of our study). In other words, oscillations can not only implement ‘ticks’ but also additionally provide the space for storing the estimated duration. According to our results, oscillations may not necessarily serve as passive pace-keepers, but they can be actively involved in the processing of time.

Moreover, our study suggests that time perception can be considered as a higher-level capacity that emerges from monitoring the activities and interactions of other neurons. This is in agreement with the second-order abstracted representation of time proposed by van Wassenhove (2009). In our model a counting-like mechanism is self-organized in the upper part of the CTRNN, which in fact receives no direct sensory input, but accomplishes encoding 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, as suggested by Craig (2009) and Wittmann (2009).

#### *4.1. Possible Computational Biases in the Timing Mechanisms*

A major goal of the current work was the study of interval timing, starting from a minimal set of modeler-imposed assumptions regarding the functionality of internal mechanisms. Nonetheless, there is a chance that the unavoidable decisions we have taken with respect to the implementation of our experiments may have introduced bias in the final result. In particular, certain implementation issues are known to affect how the observed mechanisms are shaped. These account for:

- the hierarchical structure of the CTRNN that promotes the modular functionality of the implemented system (Maniatakis & Tani, 2008);
- the time constant used in the implementation of CTRNN neurons and the 100 ms simulation step used in our experiments, which together have set the phase of oscillations and have reduced the applicability of the current model when different simulation steps are considered;

- the leaky integrator neuron model and the continuous processing of the CTRNN that enforces the encoding of behaviors and mental states as attractors in the internal dynamics of the CTRNN;
- the robotic embodiments that assume the integration of time-processing capacity with behavioral skills and sensory-motor processing.

Note, however, that nearly the same experimental setup has been used in our early work (Maniadakis & Trahanias, 2012) focusing on Duration Comparison, where the CTRNN did not give rise to self-organized oscillatory dynamics but a ramp-like neural activity. Consequently, there seems to be adequate evidence that the technicalities of our implementation do not impose hard constraints that strongly bias the emergent time-processing mechanisms. This is due to the fact that the main difference between the previous work and the current study regards the number of tasks considered. While the first explored only one task (aspect) of interval timing, the current study explores three different tasks (aspects), therefore accomplishing a multifaceted exploration of interval timing.

Intuitively, the inclusion of a limited number of tasks may be considered as the main external bias on the obtained results. The exploration of three timing tasks, when one can easily think of many other tasks to address a much broader set of duration-processing aspects, is likely to have affected the development of CTRNN neurodynamics. Even though we are not aware of other neurocomputational models that can simultaneously accomplish multiple tasks, we strongly believe that in order to obtain insight into interval timing mechanisms our models should address the broader possible set of timing capacities. This will improve the generalization of the timing mechanisms and will strengthen the biological plausibility of our assumptions.

In conclusion, the present computational study shows that the two main approaches for the representation of time existing today, namely the dedicated and intrinsic representations, can be effectively combined into a new comprehensive theory that integrates their key characteristics. Following our results, the two approaches should no longer be regarded as opponents, but rather as key ingredients of a more flexible representational scheme with enhanced explanatory power for real brain observations. Our future work will mainly involve experiments that will consider simultaneously a larger number of interval timing tasks in artificial systems.

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