Artificial Agents Perceiving and Processing Time

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*Abstract***—Time perception is a fundamental component of intelligence that structures the way humans act in various contexts. As action evolves over time, timing is necessary to appreciate environmental contingencies, estimate relations between events and predict the effects of our actions at future moments. Despite the fundamental role of time in human cognition it remains largely unexplored in the field of artificial cognitive systems.**

The present work makes concrete steps towards making artificial systems aware that the notion of time as a unique entity that can be processed on its own right. To this end, we evolve artificial neural networks to perceive the flow of time and to be able to accomplish three different duration processing tasks. Subsequently we study the internal dynamics of neural networks to obtain insight on the representation and processing mechanisms of time. The self-organized neural network solutions exhibit important brain-like properties and suggests directions for extending existing theories in timing neuro-psychology.

I. Introduction

The perception and processing of time is particularly new in the field of autonomous cognitive systems [1]. Temporal cognition plays a key role in many of our daily activities from recalling the past and making plans for the future, to estimating the remaining time during exams and dancing following the rhythm. Research in the emerging research branch of artificial time perception is expected to significantly contribute in implementing efficient artificial agents that will be seamlessy integrated into the heavily time structured human societies.

Interestingly, the fact that we can perceive space locations as many times as we want but we can perceive temporal moments only once, separates the notion of time from any other environemnt cue a system may observe.

In the field of timing neuro-psychology, the representations and processing mechanisms of time in the brain, remain largely unknown. Therefore, the development of human-like time dependent cognitive capacities (synchrony, turn-taking, mental time travel, temporal planning, temporal attention, etc.) into artificial systems remains an open issue.

The present study aims at the un-biased exploration of possible time representations and processing mechanisms 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. In particular, the present study considers 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 [2] and Learning to Time [3]. These theories assume that the behavioral vocabulary of subjects supports duration perception, a view that has been also supported by recent experimental work [4].

We employ a Continuous Time Recurrent Neural Network (CTRNN) [5], [6] to develop an "artificial brain" for the robotic agent. An evolutionary design procedure based on Genetic Algorithms [7] 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.

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 be also valid for interval processing in the brain. 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.

The rest of the paper is structured as follows. The next section summarizes the experimental setup, describing the simulated robot and the artificial brain used to endow it with cognitive and behavioral capacities. Then, we describe the behavioral tasks considered in the present work, and 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.

II. Experimental Setup

A. 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 robot bumping 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 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 (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.

A three-level Continuous Time Recurrent Neural Network (CTRNN) [5], [8] 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. 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 model. Synaptic weights are determined by an evolutionary procedure (described below) and they remain constant during task testing. Similar to previous studies [9], [10] 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 γ_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.

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 neural state by eq (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 θ_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 one of the two wheels is determined by a pair of neurons operating according to the flexor/extensor principle (i.e., one is increasing and the other is decreasing 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:

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

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

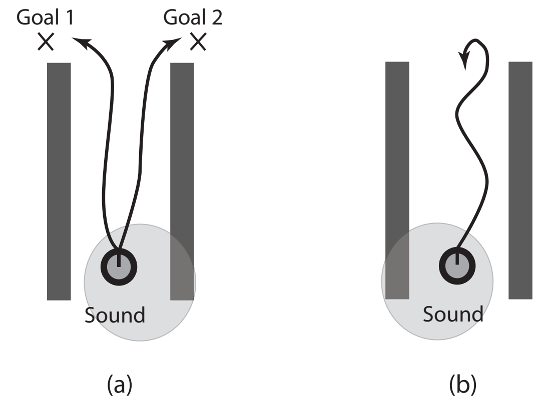

Fig. 1. A graphical representation of the experimental setup. The robot is depicted as a small circle in the bottom of the corridor. Depending on the task, the robot is asked to either reach one of the two goal positions as shown in part (a), or make a sudden 180^o turn as shown in part (b).

III. 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 [11]–[13]. 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 [14]. In the present study we explore both of these types, considering additionally a simplified example of past time-stamping.

A. 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 Figure 1(a)).

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 Figure 4(a)). 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

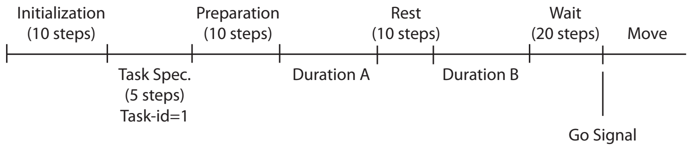

Fig. 2. The structure of the Duration Comparison task.

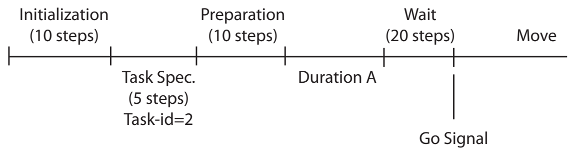

Fig. 3. The structure of the Duration Reproduction task.

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 approximately reach $Goal1$, but when $A > B$ the agent should approximately reach $Goal2$). 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:

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

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:

$$FIT_{DC} = S_{A>B} \cdot S_{A<B} \tag{5}$$

B. 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^o turn as shown in Figure 1(b).

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 4(b)). 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 at 180^o degrees, and continue navigation facing the bottom of the corridor.

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 in a sequence

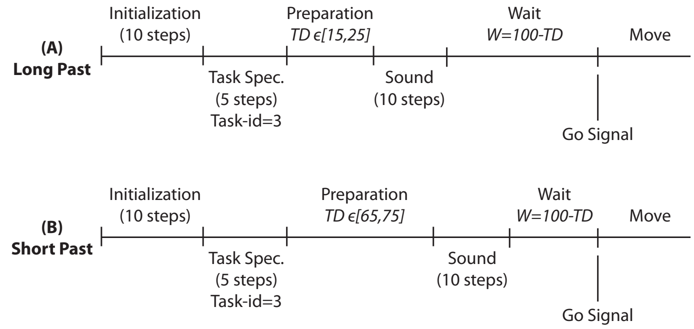

Fig. 4. The structure of the Past Characterization task.

of actions, we examine 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 at approximately 0^o degrees. Just after the completion of the A and for the next 30 steps, the robot must turn to the opposite direction steering at 180^o degrees. The success of the agent on the duration reproduction task is numerically evaluated by:

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

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

C. 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 short or 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 Figure 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 Figure 4(c)). Subsequently, a preparation interval followes 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 the emittion of sound, a wait 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 long or short time ago.

At the end of the wait 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 have been also considered in the Duration Comparison experiment (see Figure 1(a)). Depending on whether the sound has been actually experienced by the agent in the distant or 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 robot's response we use two succes measures $S_{distant}$ and S_{recent} defined according to eq. 4. Overall, the capacity of the robot to accomplish the Past Characterization task is estimated as:

$$FIT_{PC} = S_{distant} \cdot S_{recent} \tag{7}$$

IV. Evolutionary Design

We employ a Genetic Algorithm (GA) to explore possible cognitive mechanisms that enable the artificial agent to perceive and process time accomplishing the three behavioral tasks described above [7]. 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:

$$F = FIT_{DC} \cdot FIT_{DR} \cdot FIT_{PC} \tag{8}$$

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 [7]. 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. 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.

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.

V. 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. 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 have been statistically independent, all obtained results show (qualitatively) similar internal mechanisms. Below we discuss the characteristics that are common between successful artificial brains.

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 duration 45 and 60 simulation steps is shown in Figure 5(a). The robot, rather than navigating in the middle of the free corridor space and then turning either left or right, adopts a motion strategy that very early distinguishes between the two options. 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 Figure 6. 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. 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 it is suggested by dedicated timing representations [15], [16]. 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 to the theories promoting a strong correlation between embodiment and time perception [4], [17], [18].

Besides the fact that the task is clearly separated into two distinct phases of (i) perception and (ii) action, in Figure 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 to time perception. The neurons supporting ordinary cognitive tasks undertake additionally the responsibility of encoding the flow of time as it is suggested by intrinsic time representations.

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 Figure 6). This suggests that duration may be encoded in the amplitude of the oscillatory activity.

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 Figure 5(b).

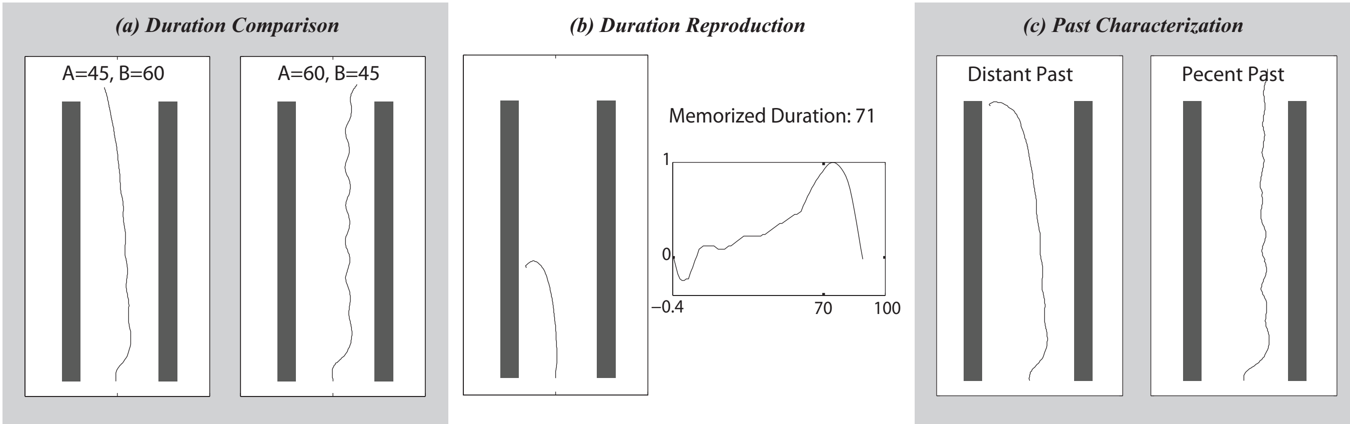

Fig. 5. The behavioral responses of the robot in the three tasks considered in the present study. Part (a) regards Duration Comparison. In the first case the robot compares intervals A and B with durations of 45 and 60 simulation steps respectively. In the second case the robot compares intervals A and B with durations of 60 and 45 simulation steps. Part (b) regards 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 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. The bell curve is centered at 74 simulation steps which indicates that the robot reproduces the memorized duration with sufficient accuracy. Part (c) regards Past Characterization task. The two plots show that the robot responds corectly to the experience of sound either in the distant or recent past.

To assess the accuracy of duration reproduction we examine how the direction of robot's motion evolves over time. The second plot of Figure 5(b) 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 robot's motion indicating that the robot moves approximately at 0^o degrees (i.e., $sin(0^o) = 0$). 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 robot's direction (i.e., $sin(90^o) = 1$), which soon after that drops again to approximately zero (i.e., $sin(180^o) = 0$). According to the second plot of Figure 5(b), the robot's turn is centered on 74, indicating that the robot has approximatelly 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 follow also oscillatory patterns, but we concentrate the discussion on the upper layer of the network which exhibits more time-relevant activity). The two black vertical lines shown in Figure 7 (a) 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. Note that a full reset of interval counting at the end of the sound experiencing phase [19], 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.

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 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 one of the two cases is shown in Figure 5(c). 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 one of the two cases is shown in the two plots of Figure 7 (b) 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 count-down 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 Figure 7 (b)). This increase is followed by reverse counting that continues until the amplitude has a sufficiently low value, indicating that it was long time ago since a sound was experienced. In the recent past condition (see the plot of Figure 7 (c)) the amplitude of the sinusoidal increases again with the emision 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 im-

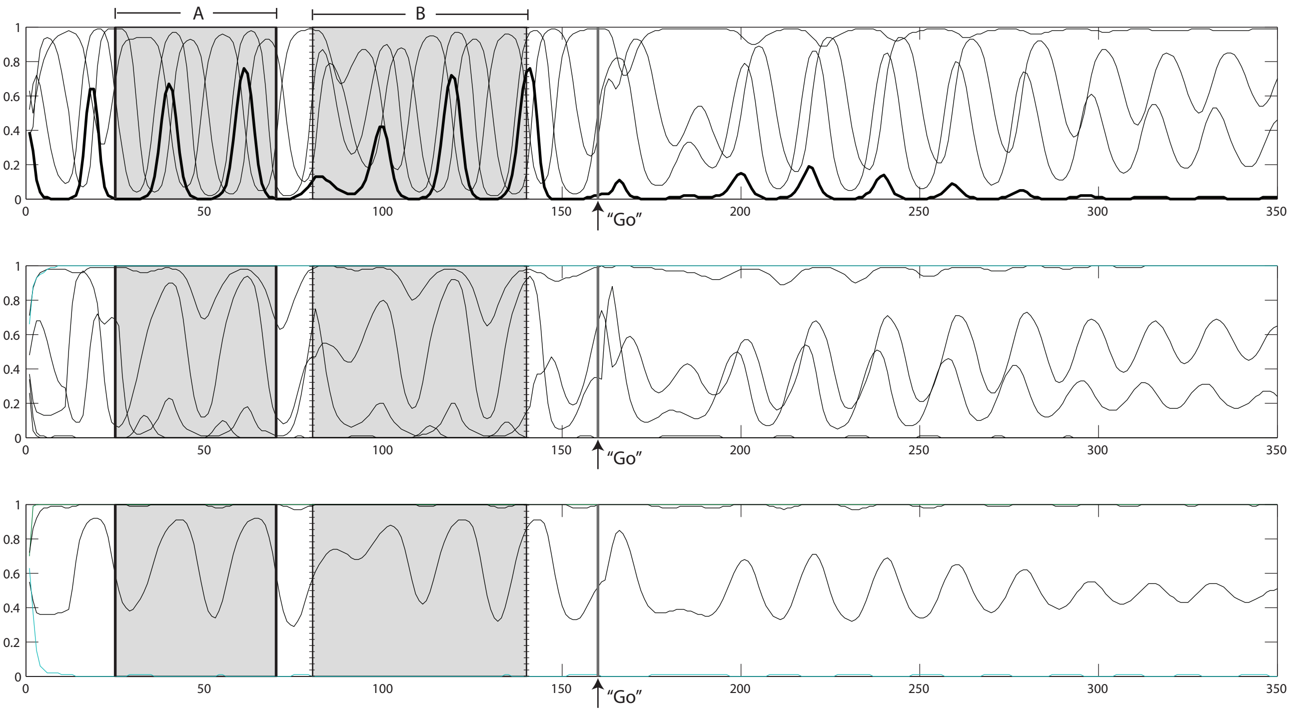

Fig. 6. The neural activity in the three layers of the of the CTRNN during a Duration Comparison task with A=45 and B=60. Each plot corresponds to a different layer of the CTRNN.

plements diverse behavioral responses for the two cases of past characterization (see Figure 5(c)). In other words, the amplitude of oscillatory neural activity can not only operate as a possible accumulator, but may also integrate an inverse counting capacity, therefore being actively engaged in decision making.

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 [5]. 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 clock-like 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 bottom side of the corridor to indicatethe 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 occurs 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.

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 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 interval timing mech-

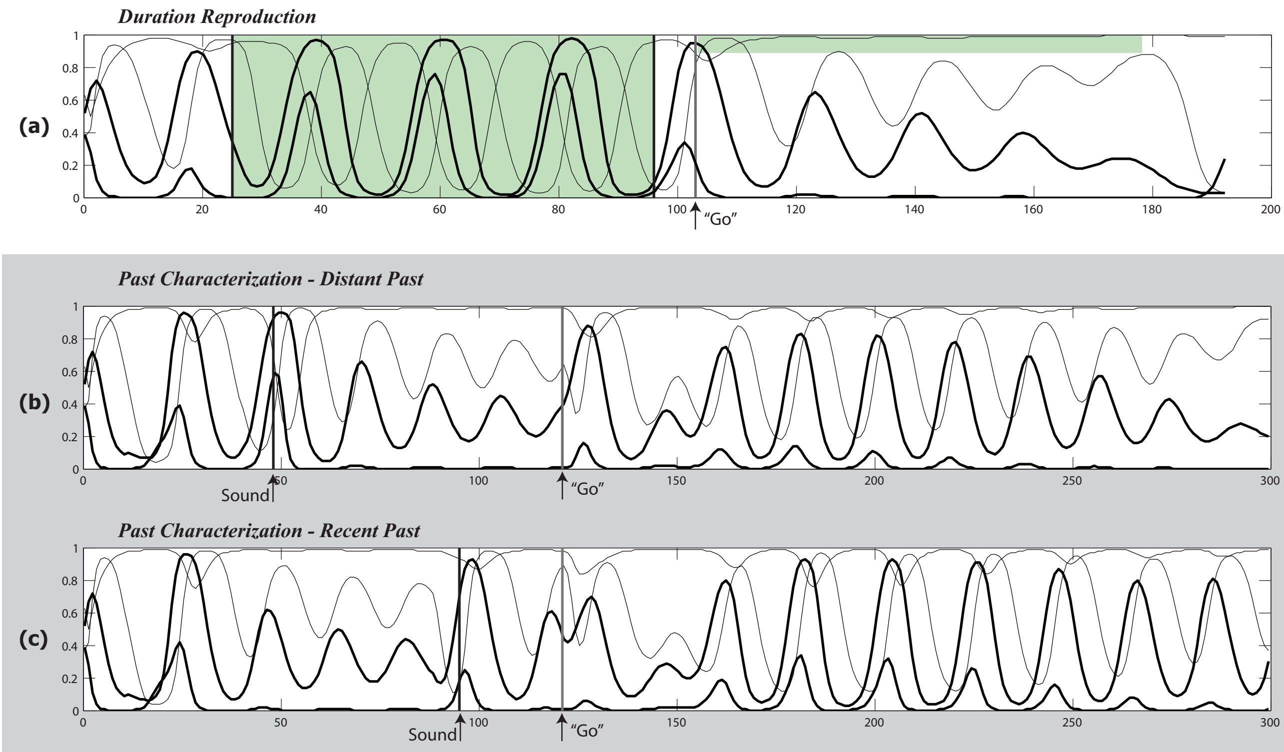

Fig. 7. The activity in the upper layer of the CTRNN in (a) the Duration Reproduction task where the length of the perceived and reproduced interval is depicted with a gray box, (b) the Past Characterization task for the case of time experiencing in the distant past, and (c) the Past Characterization task for the case of time experiencing in the recent past.

anism that emerges from our model is in agreement to the proposal for a higher level representation of duration [20].

VI. Discussion and Conclusions

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 [21], [22]. 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 on 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 [15], [23], [24]. This has inspired the subsequent pacemaker approach that uses oscillations to represent clock ticks [16], [25]. Other dedicated models assume monotonous increasing or decreasing processes to encode elapsed time [26], [27]. The second approach includes intrinsic explanations (also known as distributed) that describe time as a general and inherent property of neural dynamics [28], [29]. 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 [**?**], [30]. 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 regards its weakness in explaining modality specific differences in time perception. On the other side, 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 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 the intrinsic time representation. So far, the main argumentation against intrinsic approaches [29] 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., [26]). 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 [15], [16]. However, our model shows that duration can be encoded in the parameters of the oscillatory activity (in the amplitude of the oscillation for the case of our study). In other words, oscillations can not only implement "ticks" but 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.

Therefre, 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.

Following our results, the dedicated and intrinsic representations of time 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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