Experiencing and Processing Time with Neural Networks

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Abstract—The sense of time is directly involved in most of the daily activities of humans and animals. However, the cognitive mechanisms that support experiencing and processing time remain unknown, with the assumption of the clock-like tick accumulation dominating the field. The present work aims to explore whether temporal cognition may be developed without the use of clock-like mechanisms. We evolve ordinary neural network structures that (i) monitor the length of two time intervals, (ii) compare their durations and (iii) express different behaviors depending on whether the first or the second duration was larger. We study the mechanisms self-organized internally in the network and we compare them with leading hypothesis in brain science, showing that tick-accumulation may not be a prerequisite for experiencing and processing time.

Keywords-time perception, temporal cognition, brain-inspired cognition, robotic system

I. INTRODUCTION

The interaction of humans and animals with the environment is supported by multiple sensory modalities such as audition, vision and touch, each one mapped on a specific region of our brain. Interestingly, our sense of time relies on radically different working principles breaking the rule of using a dedicated brain region for processing. Humans and animals lack "time sensors", as well as a primary sensory brain area devoted explicitly to the sense of time [1].

Time experiencing has attracted significant research interest in brain science, with several works considering where and how time is processed in our brain [2], [3]. An extensive number of brain areas have been reported to contribute in time experiencing such as the cerebellum [3], the right posterior parietal cortex [4], the fronto-striatal circuits [5], the insular cortex [6] and the medial temporal lobes [7].

There are now two main explanations on how our brain experiences time [8]. The oldest and most influential approach assumes the existence of pacemakers producing tick sequences which are counted by an accumulator. A modern version of this assumption assumes coincidence detection circuits to operate as timekeepers [9]. The alternative approach assumes that time may be encoded in the dynamic state of neuron populations that support ordinary cognitive processes. This implies that our brain does not need pacemakers or timekeepers to experience the flow of time. Still, it remains unclear whether such a neural-state-based mechanism may robustly support the accomplishment of behavioral and cognitive tasks.

The present work aims to investigate the reliability of the latter clock-free approach with respect to a time-based behavioral task, exploring also the possible benefits that a cognitive system may gain from adopting such a dynamical state approach. To address this issue, we employ self-organized computational cognitive systems embodied in artificial agents. Our study focuses on a task that considers comparing the length of two time intervals. The underlying task assumes agents capable of experiencing the flow of time, monitoring and measuring the time elapsed, encoding the duration of the first interval in working memory and contrasting the first and second temporal durations, in order to choose between alternative response activities. To develop such a capacity, we evolve Continuous Time Recurrent Neural Networks and we investigate the dynamics self-organized in the networks in order to reveal the mechanisms encoding and comparing the two temporal intervals. This is expected to promote one of the alternative hypothesis of time processing in the brain. Note that brain scientists have recently considered embodiment as a key feature for the emergence of time perception capacity (e.g., [6], [8]), therefore making robotic experiments particularly appropriate for investigating time processing mechanisms.

In the field of artificial intelligence the role of time in cognition is currently not adequately appreciated [10]. More than a decade ago, F. Varela discussed the fundamental role of time flow experiencing in cognition [11], without however accomplishing to direct scientific interest on artificial time perception. Existing systems can only superficially consider time in their cognitive loop. For example, a turn-taking task with two agents accomplishing to synchronize their behavior, changing roles periodically is studied in [12]. In another experiment, an artificial cognitive system self-organizes mechanisms that consider and exploit time, in order to develop high level cognitive skills such as executive control [13]. However, to the best of our knowledge, no artificial cognitive system has been implemented capable to explicitly process time in order to accomplish a behavioral task. The present study aims to fill this gap, paving the way for artifcial agents with human-like time processing capacity (e.g., perceive synchrony and ordering of events, mentally travel in the past and future, share with humans temporal views about the dynamic world).

In the following sections we first describe the task consider in our study and the method used to design neural network based cognitive systems. Subsequently, we present the obtained results and the mechanisms self-organized in neural networks. Finally, we discuss how our findings may compare to time-related brain processes and we provide directions for future work.

II. EXPERIMENTAL SETUP

The present experiment investigates mechanisms capable of (i) experiencing the flow of time and (ii) comparing temporal intervals. We have implemented a simulated environment which involves a two wheeled simulated robotic agent equipped with 8 uniformly distributed distance and light sensors. The agent experiences a light cue for two different intervals A and B. A Continuous Time Recurrent Neural Network (CTRNN) is used to provide the artificial agent with cognitive capacity. The CTRNN is evolved to experience the flow of time, compare the two intervals A and B, and implement alternative robotic behaviors depending on whether A or B was longer. Note that the robotic behaviors considered in our experiments are kept in rather low levels of complexity in order to direct focus on the mechanisms supporting the experience and processing of time.

A. Behavioral Task

The experiment starts with a simulated mobile robot located at the beginning of a corridor environment (see Figure 1). The artificial agent remains at the initial position where it experiences the same light cue for two different time intervals A and B. The agent has to consider and compare the durations of A and B to decide which one is longer. Then, in order to successfully complete the task, the agent has to navigate to the end of the corridor and turn right when the A interval was longer, or, turn left when the A interval was shorter (than B).

The temporal structure of the experimental procedure is illustrated in Figure 2. The trial starts with a short preparation phase making the internal state of the CTRNN obtain a non-random initial value before light experience begins. Just after that, the first light experience is provided to the agent, which last for a randomly specified number of simulation steps (in the range [10,100]), corresponding to the length of the temporal interval A. Subsequently the agent rests for ten simulation steps and then it experiences light for a second time, which corresponds to the second time interval B (that is again randomly specified in the range [10,100]). Then the agent is provided 20 simulation steps to decide the response direction. At the end of the wait period the agent is provided a "go" signal and then it starts navigating to the end of the corridor turning left or right. We note that we preserve a minimum distance of 15 simulation steps between the A and B intervals, to ensure that the agent will be capable of comparing all randomly generated pairs of A and B.
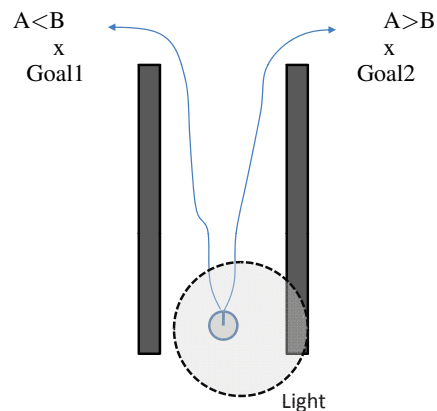

Figure 1.   Graphical illustration of the experimental setup . The agent experiences light for two temporal intervals A, B and depending on which one was longer it has to drive either leftwards, or rightwards.
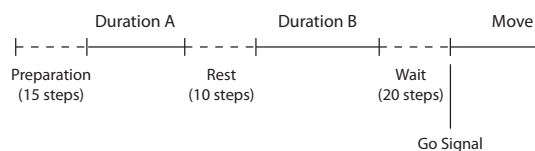

Figure 2.   The temporal structure of the experiment.

B. CTRNN Model

We use a Continuous Time Recurrent Neural Network (CTRNN) model to investigate how time experiencing and processing mechanisms self-organize in neuronal dynamics. The implementation of the CTRNN is based on the well known leaky integrator neurons as it is described in previous studies [14]. Interestingly, in CTRNNs information is implicitly encoded using internal neurodynamics. Thus, in our experimental setup, the neuronal state is initialized only once in the beginning of the trial, and then neuronal dynamics continue without resetting.

In the present work we use a two-layer neural network (with full connectivity within and among layers), as shown in Figure 4(a). The upper layer receiving sensory information is expected to monitor environment changes self-organizing a time processing capacity, and additionally implement the mechanism for comparing A and B. For the purposes of the present study this layer is considered as the core component of the CTRNN. The lower part of the network aims to combine the result of the A and B comparison with the current sensory input in order to effectively drive the robotic agent along the corridor.

C. Evolutionary Procedure

We employ a Genetic Algorithm (GA) to explore cognitive dynamics enabling the artificial agent to perceive the flow of time and additionally compare the length of the two time intervals A and B. We use a population of

1000 artificial chromosomes encoding different CTRNN configurations (their synaptic weights and neural biases). Each candidate CTRNN solution is tested on eight randomly initialized versions of the task described in the previous section (randomness regards the lengths of A and B intervals). In the first four tasks, the duration of A was longer than B, while the opposite relation holds for the last four tasks. The evaluation of CTRNNs in multiple random tasks has been shown to significantly improve the validity of the evaluation metric, while at the same time it increases the robustness of the evolved cognitive system against difficult exemplar scenarios.

To evaluate the capacity of the artificial agent in comparing the length of temporal intervals A and B, we mark two different positions in the environment which are used as goal positions for agent's behavior, as shown in Figure 1. Depending on whether A has been actually longer than B or not, we select the appropriate goal position and we measure the minimum distance D of the agent's path from that goal (i.e., when A>B the agent should approximate Goal1, while when A<B the agent should approximate Goal2). Additionally, during navigation, we consider the number B of robot bumps on the walls. Overall, the success of the agent to accomplish a given task i is estimated as:

$$S_i = \frac{100}{D \cdot B} \qquad (1)$$

By maximizing S_i, we aim at minimizing the distance from the goals producing responses at the correct side of the corridor, as well as avoid bumping on the walls. Then, the total fitness of the individual for the combination of eight randomly initialized tasks is estimated by:

$$fit = \prod_{i=1}^{8} S_i \qquad (2)$$

The afore mentioned measures guide the evolution of the randomly initialized population consisting of 1000 individuals, each one encoding a complete CTRNN configuration. Real-value encoding is used to map synaptic weights and neural biases into chromosomes. We have used a standard GA process with survival of the fittest individual along consecutive generations. During reproduction, we have used as a basis the best 30 individuals of a given generation, which randomly mate with the 70% of the rest individuals using a single point crossover. Mutation corresponds to the addition of up to 25% noise, in the parameters encoded to the chromosome, while each parameter has a probability of 4% to be mutated. In each evolutionary run the randomly initialized population is evolved for a predefined number of 500 generations.

III. RESULTS

We have evolved CTRNN controllers running eight different GA processes. Five of the evolutionary procedures
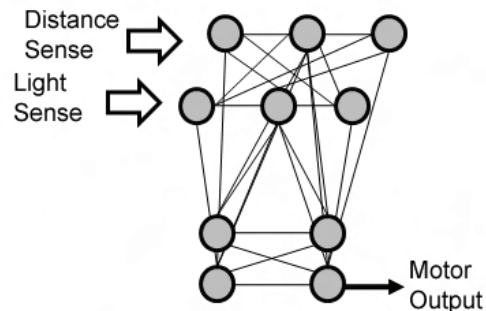

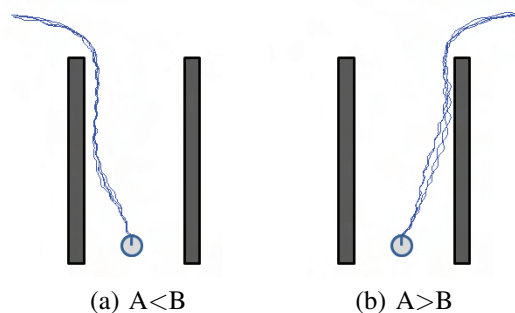Figure 3. The CTRNN used in the present study.

(a) A<B (b) A>B

Figure 4. Parts (a) and (b) correspond to the results of the evolutionary procedure showing the two different types of responses provided by the agent when A<B, or A>B.

converged successfully configuring CTRNNs capable of comparing temporal intervals, accomplishing the behavioral task described in the previous sections. Interestingly, the results obtained from the statistically independent evolutionary procedures exhibit common characteristics, which are discussed below using as a working example one representative solution. The performance of the agent in comparing two time intervals successfully driving to the correct side of the corridor, is demonstrated in Figure 4 (a) and (b).

Note that the experience of time intervals and the estimation of their length is mainly implemented in the upper component of the CTRNN. The motor component of the network seems to have no contribution in measuring the length of time intervals being mainly involved in implementing the motor response. Therefore, we concentrate on the upper part of the CTRNN for the rest of our study.

In order to obtain insight in the dynamics self-organized internally in the CTRNN, we have conducted tests revealing the memorization and comparison mechanisms. Following the symbolization [A vs B] to denote the durations of A and B intervals considered in a particular test case, we have examined the following exemplar tests with A shorter than B: [10 vs 25], [20 vs 40], [20 vs 70], [40 vs 60], [80 vs 95] as well as test cases where A is longer than B: [25 vs 10], [40 vs 20], [70 vs 20], [60 vs 40], [95 vs 80]. The

activation of neurons in the upper part of the CTRNN for the aforementioned pairs of [A vs B] tests is depicted in Figure 5. We see that the obtained solution is sufficiently robust, dealing successfully with the cases of A and B being both short or both long, as well as with other intermediate comparisons. In all shown plots we can easily identify the A and B period that the agent experiences light, followed by a sinusoidal activation which corresponds to the navigation of the agent to the end of the corridor turning either left or right. For example, in the second plot of the first column of Figure 5 considering [20 vs 40] the agent experiences the first period of light from step 15 to step 35, then rests for 10 steps, and experiences the second period of light from step 45 to step 85. In the next 20 steps it has to decide the direction of the given response, and implements the underlying response from step 105 until the end of the trial.

Monitoring the Elapsed Time. With a close look into the dynamics implemented in the upper component of the CTRNN, we see that three neurons are employed to measure the length of temporal intervals. This corresponds to the neurons plotted in red, green and magenta in Figure 5. We observe that these three neurons start diminish their activities one after the other as time passes, which suggests that the agent segments the time flow at bins of approximately 25 simulation steps (see for example the last plot in Figure 5). This type of segmentation facilitates counting the length of the experienced light intervals and the aggregation of the time elapsed. We note that similar time related ramping activity (in fact, it is an inverse ramp in our model) has been observed in many brain areas being probably involved in time processing [15], [16].

Note that measuring the elapsed time for the case of interval B, is affected by the length of interval A. For example, compare the way that the 40-steps interval is experienced in the second plot of Figure 5 (a) and in the fourth plot of Figure 5 (b). Clearly, the given interval of 40 simulation steps is experienced in two different ways. This is because the internal state of the network as it is shaped at the end of A, modulates the experience of B. As it is explained below, this perceptual adjustment is implemented in order to facilitate comparison.

Decision Making. In order to obtain insight on how the CTRNN decides the longest of the two intervals, we conduct principal component analysis in the neural activity of the upper level. The activity of the first principal component (PC1) for the test cases discussed above is illustrated in Figure 6. Clearly, the longer interval (either A or B) is the one that implements the lower PC1 values. Note that the shortest the length of the first interval, the steepest the decrease of PC1 in the begging of the second interval, while in contrast when the first interval is long then PC1 diminishes slowly when B is experienced. This means that the network memorizes the length of the A period by undertaking neural states that properly modulate the ways

the second interval is experienced. In other words, a 20 steps interval is not the same when it is experienced first or second in order. This is in agreement to the subjective experience of time and the modulation of duration perception in humans by external factors such as attention, or emotions.

Turning back to Figure 5, we observe that the neurons being responsible for comparing the two temporal intervals and deciding the direction of robot's motion are mainly the ones plotted in red and black. Every time that the agent concludes "B is longer" the black neuron activity is high and the red activity low (Figure 5 (a)). However, when "A is longer" these two neurons do not have enough time to take extreme high and low values (Figure 5 (b)). Interestingly, the same neurons hold also an estimate of the final decision at the intermediate rest period of the agent. When the first interval is short, then the neurons predict that a probably longer one will follow decreasing the activity of the underlying neurons at the beginning of B (see for example the first and second plot in Figure 5(a)). In contrast when the agent has experienced a long A, the agent predicts that the second period will be probably shorter, setting both neurons to relatively high values at the beginning of B (see for example the last plot in Figure 5(b)).

Adjustable Duration Comparison. When A is short, it is easy for the network to compare it with a long B, but it is difficult to compare it with a short B. To address this issue, the network adjusts the way B is experienced. In particular, a short A results into fast neural changes in the early B steps, magnifying possible differences between a short A and a short B. See for example neural activities in the first plot of the Figure 5 (a) where both A and B are short. The other case of B being long, can be easily handled with clear neural differences as it is shown in the third plot of Figure 5(a).

In the other extreme case where both A and B are long, we see that neural changes are slow at the early steps of B making the network shift focus at a later time, magnifying the difference between the two intervals when the length of B approximates the length of A. See for example the last plot in Figure 5(a) where fast neural changes are observed mainly at the end of the B interval. The case of A being long and B short can be easily handled with clear neural differences, as it is shown in the third plot of Figure 5(b).

Overall, following the above described adjustments, depending on the length of A, the network accomplishes to direct focus on the moments that are more critical for a given comparison.

Motion Planning and Action Implementation. The direction of the motor response is decided by the upper part of the CTRNN. Note that the main difference in neural activity between the cases that the agent moves left-wards or right-wards, is the unfolding of the neuron plotted in blue (compare the plots shown in Figs 5(a) and 5(b)). We observe a clear oscillation of the underlying neuron when the agent drives left, while the activity of the neuron vanishes when
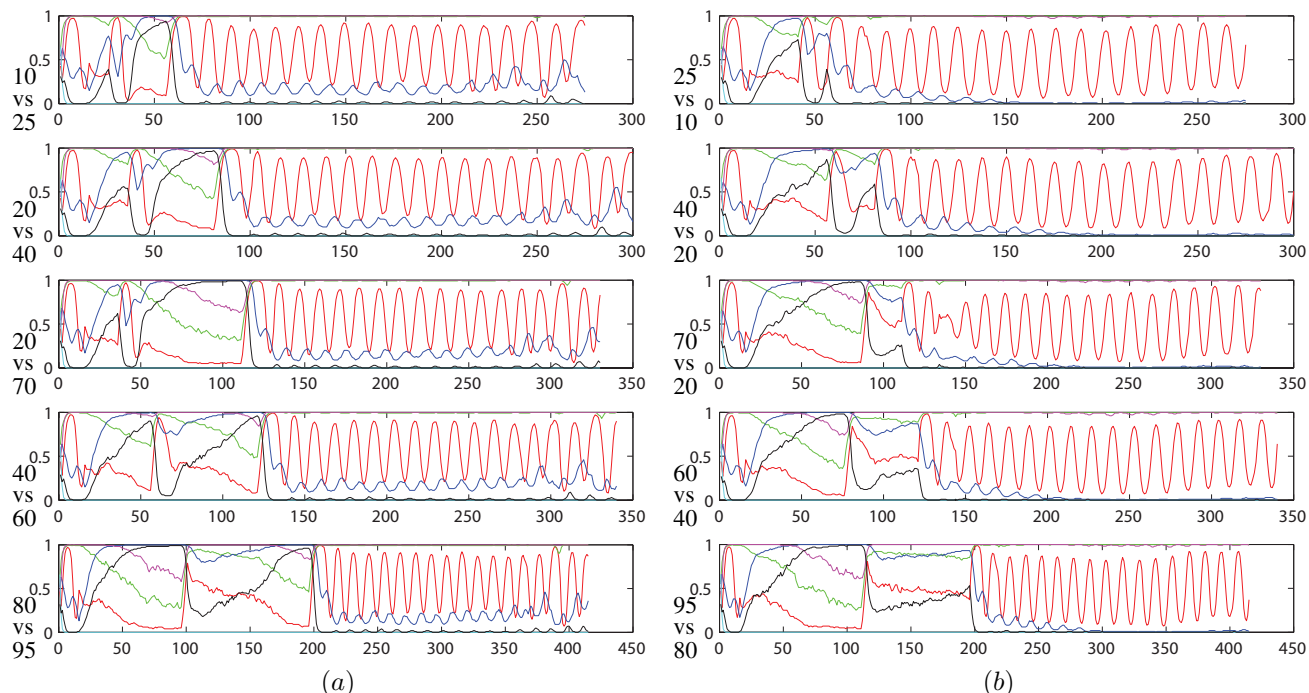
Figure 5. The activity of neurons in the upper level of the CTRNN for several test cases with the duration of interval A being shorter than B in column (a) and A being longer than B in column (b).

the agent moves right.

IV. DISCUSSION

The present work explores time processing cognitive mechanisms considering whether they require clock-like "tick" signals to work. According to our findings, cognitive systems can solve duration comparison tasks without using any tick-based mechanism. Our model has developed another time measurement mechanism with an (inverse) ramp functionality similar to the one observed in the brain [15], [16]. Despite the fact that the implemented system adopts oscillation-based internal mechanisms for driving the robot, the experience of time is based on rate coding rather than a mixture of oscillations. This contrasts the neuroscientific assumption arguing that time experiencing relies on monitoring the neurons oscillating in our brain at different rates [2].

As it is explained above, the CTRNN model implements an adjustable way to experience time, which facilitates duration comparison. This is in agreement with modern approaches explaining time-experience on the basis of dynamic neural states [17]. According to our results, experiencing a given time interval is not accomplished in a universal, flat way and is not always the same, but it is rather modulated by the state of the network at the beginning of time experiencing. The present work reveals a beneficial characteristic of such a flexible time experiencing mechanism which regards the ability of the network to properly focus on the most critical moments of a given comparison accomplishing to

solve the task for difficult exemplar cases (i.e., compare A and B having small duration difference).

V. CONCLUSIONS

The current work investigates possible mechanisms for time perception in cognitive systems. We show that ordinary neural schemes can self-organize robust mechanisms for monitoring, representing and comparing two different temporal intervals developing at the same time biologically reliable characteristics. Our findings suggest (i) that pacemakers is not the only possible solution for experiencing and processing time, and (ii) that adaptive time perception may be beneficial for the functionality of the overall system enabling to direct attention on the most critical time moments.

The current work may serve as a basis for more sophisticated computational models developing the full extent of time processing skills. In the near future we intend to extend the implemented model in the direction of ordering perception, and time-based recall.

Interestingly, time processing models may be also embodied in robotic systems to improve their cognitive capacities. Due to the central role of time in a range of different modalities, such as experience encoding and learning, the use of tenses in natural language, long term action planning, etc., the implementation of artificial agents that perceive and process temporal information has a great potential towards the seamless integration of robots in human societies.
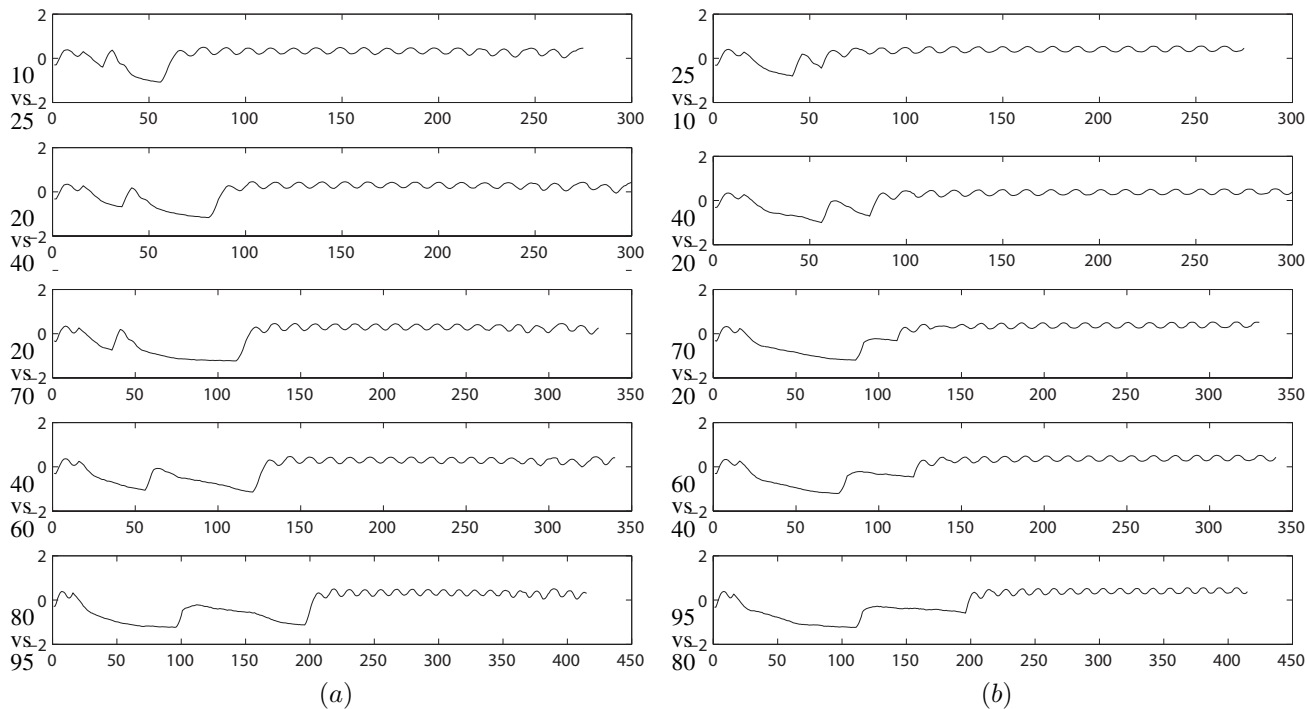
Figure 6. The activity of the first principal component in the upper level of the CTRNN, shown for several test cases with the duration of interval A being shorter than B in column (a) and A being longer than B in column (b).

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