Inspiration from Neurosciences to emulate Cognitive Tasks at different Levels of Time

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Abstract

Our team has been working for more than ten years on the modelling of biologically inspired artificial neural networks. Today, our models are used to different cognitive tasks like autonomous behavior and exploration for a robot, planning, reasoning, and other tasks linked to memory and internal representation building. We present the framework that underlies these models through the time delays related to several fundamental properties like information coding, learning, planning, motivation.

1 Introduction

The goal of this poster is to present one original consequence of getting inspired by biology to elaborate temporal mechanisms for behavioral modelling. More precisely, symbolic or numerical tools for temporal processing are generally applied to very specific tasks like for example high level planning, perceptive scene analysis or temporal alignment of speech signal. It is then quite impossible to integrate these models to get the corresponding full range of properties, necessary for the implementation of a realistic task including these various levels of time. One important advantage of using biologically inspired neural networks for temporal processing is that biology offers a complete framework of inspiration from the lowest to the highest levels of time scale.

2 The bit level

At the level of 10^0 millisecond, a neuron can perform synaptic transmission to its closest neighbors. One millisecond is also the duration of a spike. At the neuronal level, this time scale is thus the level of the lowest bit of information. This level of neuronal processing is deeply studied in the so-called "spiking neuron" approach Maass and Bishop (1998). Here, a model of neuron is considered as an elementary unit emitting spike trains. At the synaptic level, Grossberg (1984) proposes differential equations to model neurotransmitter consumption and production, whose equilibrium state yields a non-linear function, similar to classical sigmoidal transfer function.

3 The coding level

At the level of 10^1 milliseconds, the duration of the interval between two spikes can be evaluated, since, in the central structures, the neuronal maximal frequency cannot exceed 100 Hz. Whereas classical connectionist approaches Hertz et al. (1991) generally use continuous models of neurons, whose activation value corresponds to the estimated mean frequency of spike trains, the spiking neuron approach deepens the idea that, as spike emission is a binary process, all the neuronal information is included in the timing of the spikes. Beyond simple frequency estimation, other rate coding or even phase coding can be also investigated at this level of description Maass and Bishop (1998). At the behavioral level, this time scale corresponds to inter-areal communication including for example feedback information and focus of attention.

4 The processing level

At the level of 10^2 milliseconds, the activation dynamics of a population of neurons can stabilize into a synchronized state. This phenomenon can be precisely studied with spiking neurons. For example, Mar et al. (1999) investigates how a population of coupled model neurons can perform noise shaping. The population of neurons is such an important and consistent level for neuronal processing that several researchers like Edelman (1987); Burnod (1989); Alexandre et al. (1991) have chosen this level of description to define an integrated neuronal automaton which thus corresponds to a synchronized population of neurons.

At the behavioral level, this time scale corresponds to the stabilization of activity consecutive to oscillations created by sensory and motor events, from the first to the last processing layer. This duration can thus allow to perform recognition or action in elementary sensorimotor loops, thanks to the integration of activity in these layers. Koechlin and Burnod (1996) describes this phenomenon in models ranging from the spiking neuron to the integrated automaton levels.

5 The learning level

At the level of 10^3 milliseconds, neurons in the highest levels in the associative cortex can stay active for such a duration. This lasting internal representation can allow for such process as object exploration, including multimodal dimensions. Kosslyn et al. (1992) describes how a pattern can be recognized through the identification of its subparts (temporal areas) together with their localization (parietal areas).

This time scale also corresponds to learning elementary processes. From the basic idea proposed by Hebb Hebb (1949) as soon as 1949, stating that reinforcement can be produced by presynaptic and postsynaptic activity coincidence, many elaborated learning rules have been proposed. Among them, some try to integrate a temporal dimension to this rule, allowing presynaptic and postsynaptic activities to be consecutive and not simultaneous. These rules generally use the trace signal principle Reiss and Taylor (1991), yielding a lasting and progressively extinguishing activity when the signal is no longer present. This lasting activity can make two separate signals meet and perform learning. This idea was for example exploited in Sutton and Barto (1981) to model pavlovian conditining.

6 The stack level

At the level of 10^4 milliseconds, neurons in the frontal cortex can have a sustained activity which is the basis for working memory in this region. Burnod (1989); Fuster (1996) describe how the control of bistable activity in frontal neurons can allow to build stacks that can command the triggering of sensorimotor events in the posterior part of the cortex. More precisely, the temporal organization of behavior can be performed with such a mechanism, as shown by computer science implementation by Guigon et al. (1995) for monkey conditioning paradigm modelling or by Frezza-Buet and F. (1998) for environment exploration by an autonomous robot.

7 The modulation level

At the level of 10^5 milliseconds and more, rhythms can be produced by extra-cortical structures like the reticular formation or the hypothalamus. Neuronal intrinsic metabolic and genetic processes can occur at such very long time constants and influence cortical activity. This level can thus be defined as the level of emotion, motivation, mood and other global influences that can regulate the whole behavior. As proposed in Burnod (1989), such modulatory phenomena can be modelled through global variables, able to influence the whole network.

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