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Gated spiking neural network using Iterative Free-Energy Optimization and rank-order coding for structure learning in memory sequences (INFERNO GATE)

Alexandre Pitti *, Mathias Quoy, Catherine Lavandier, Sofiane Boucenna

Laboratoire ETIS UMR 8051, Université Paris-Seine, Université de Cergy-Pontoise, ENSEA, CNRS, France

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A B S T R A C T

We present a framework based on iterative free-energy optimization with spiking neural networks for modeling the fronto-striatal system (PFC-BG) for the generation and recall of audio memory sequences. In line with neuroimaging studies carried out in the PFC, we propose a genuine coding strategy using the gain-modulation mechanism to represent abstract sequences based solely on the rank and location of items within them. Based on this mechanism, we show that we can construct a repertoire of neurons sensitive to the temporal structure in sequences from which we can represent any novel sequences. Free-energy optimization is then used to explore and to retrieve the missing indices of the items in the correct order for executive control and compositionality. We show that the gain-modulation mechanism permits the network to be robust to variabilities and to have long-term dependencies as it implements a gated recurrent neural network. This model, called Inferno Gate, is an extension of the neural architecture Inferno standing for Iterative Free-Energy Optimization of Recurrent Neural Networks with Gating or Gain-modulation. In experiments performed with an audio database of ten thousand MFCC vectors, Inferno Gate is capable of encoding efficiently and retrieving chunks of fifty items length. We then discuss the potential of our network to model the features of working memory in the PFC-BG loop for structural learning, goal-direction and hierarchical reinforcement learning.

1. Introduction

1.1. Proposal framework for sequence learning

In this paper, we propose to use the neural architecture Inferno, standing for Iterative Free-Energy Optimization in Recurrent Neural Network, for the learning of temporal patterns and the serial recall of sequences (Pitti, Gaussier, & Quoy, 2017; Pitti, Quoy, Lavandier, & Boucenna, 2019). We originally proposed this neuronal architecture to model the cortico-basal ganglia loop (Pitti et al., 2017) for retrieving motor and audio primitives using Spike Timing-dependent Plasticity (STDP) within the framework of predictive coding and free-energy minimization (Friston, 2003; Friston, Kilner, & Harrison, 2006; Keller & Mrsic-Flogel, 2018). Here, we propose to implement a similar free-energy minimization network but this time in the prefrontal–basal ganglia loop for the serial recall of memory sequences and for the learning of temporal pattern primitives, using gain-modulation instead of STDP. Since this working memory uses gain-modulated or gating cells instead of STDP, we propose to name it Inferno Gate in order to disambiguate this architecture from our original network.

Gain-modulation will serve to model neurons salient to the temporal order of items and their sequential organization. As we will explain further, prefrontal units depend crucially on this type of coding for serial recall. They support a gain-modulated mechanism to jointly encode items and rank-order information in a sequence (Botvinick & Watanabe, 2007). This mechanism of gain-modulation is also described as a gating or conjunctive function in other research (Hasselmo & Stern, 2018), placing more emphasis on the properties of filtering out or holding on to information.

We will show that Inferno Gate is capable of learning temporal primitives sensitive to the serial order of items within sequences, coding abstract temporal sequences *without* information about items, and accurately retrieving sequences of items with respect to the given serial order information *only*. We think its architecture makes it robust for structural learning, model-based reinforcement learning and compositionality.

Our main contributions are to propose a neuro-computational architecture of the PFC and a novel mechanism to encode temporal sequences in an efficient way for language processing. The

* Corresponding author.
E-mail addresses: pitti.alexandre@u-cergy.fr (A. Pitti), quoy.mathias@u-cergy.fr (M. Quoy), lavandier.catherine@u-cergy.fr (C. Lavandier), boucenna.sofiane@u-cergy.fr (S. Boucenna).

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neuro-computational architecture Inferno Gate learns, recognizes and retrieves missing elements in memory sequences based on an original encoding mechanism that represents sequences with a distributed neural population of temporal primitives learnt. These temporal primitives are abstract patterns constructed from information about the rank order of the items within sequences, *without* their index per se. This new brain-inspired encoding based on spikes makes the representation of sequences more compact, the learning faster, and the retrieval of missing items more efficient than the encoding performed in conventional neural networks and possibly deep networks (Kasabov, 2018).

The paper is organized as follows. We will present first the developmental and neural foundations of our neural architecture and its purpose. In second, we will present a state of art of prefrontal models and justify how our model is original in comparison to them.

We will detail then the neural mechanisms used. We explain how an analog gating can be created with spiking neurons and how gain-modulated neurons can represent a compact code for sequences. In comparison to other gain-modulation architectures that require a one-to-one conversion matrix necessary for multiplicative binding –, which consumes neurons for this computation,– we discovered that a rank-order coding algorithm can model gain-modulation in a more efficient manner with spiking neurons.

We apply this network for the learning of temporal primitives from audio sequences. These primitives are then used for representing and recalling these audio sequences with a length of one second (1000 ms), corresponding to chunks of 50 items' length, despite information about the items' index (their content or their identity) being lost.

We then discuss the originality of our approach and implications in terms of computation for modeling sequences, extracting temporal tree structure-like patterns, and compressive coding of grammar-like models, recursive representation, compositionality and transfer of learning.

1.2. Developmental and neural foundations

During early development, infants are keen on grasping structure in several core domains (Spelke, 2003; Spelke & Kinzler, 2007), inferring causal models and making hypotheses like little scientists (Gopnik, Meltzoff, & Kuhl, 2000; Tenenbaum, Kemp, Griffiths, & Goodman, 2011). They rapidly develop knowledge about numerosity, space, physics and psychology but it is only at around 8 months that they gain the aptitude to make complex sequences and to retain structural information in their environment.

In language acquisition, this skill is central for word segmentation and for detecting grammatical and ungrammatical sentences (Saffran, Aslin, & Newport, 1996; Saffran & Wilson, 2003). For instance, infants are sensitive to the temporal order of events in spoken words and in music so that they can be surprised if one syllable is changed or if one sound is removed, violating their prior expectations (Basirat, Dehaene, & Dehaene-Lambertz, 2014).

It is at this period, too, that the prefrontal cortex (PFC) develops. The prefrontal circuits comprise a working memory for executive control and planning that evaluates sequences online based on uncertainty (Yu & Dayan, 2005), and select/unselect them according to the current context, or create new ones if any are satisfying (Daw, Niv, & Dayan, 2005; O'Reilly & Frank, 2006; Rougier & O'Reilly, 2002).

More than any other brain areas, the PFC can extract abstract rules and parametric information within structured data in order to carry out a plan (Romo, Brody, Hernández, & Lemus, 2018; Tanji & Hoshi, 2001; Wang et al., 2018). This aspect makes it particularly important for problem-solving tasks, language and maths (Dehaene, Meyniel, Wacongne, Wang, & Pallier, 2015; Koechlin, 2014, 2016; Rouault & Koechlin, 2018).

Experiments carried out on subjects performing hierarchical tasks such as drawing a geometrical figure (Averbeck, Chafee, Crowe, & Georgopoulos, 2003; Averbeck, Crowe, Chafee, & Georgopoulos, 2003) or detecting temporal patterns within action sequences (Shima, Isoda, Mushiake, & Jun Tanji, 2007; Tanji, Shima, & Mushiake, 2007) have permitted identification of some properties of PFC neurons for binding features and for higher-order sequence planning. In series of observations done on PFC neurons, a critical finding was that sequences were encoded through a conjunctive code, which crosses items and serial orders (Barone & J.P., 2018; Ninokura, Mushiake, & Tanji, 2004). In similar experiments performed by Inoue and Mikami, some PFC neurons were found to modulate their amplitude level with respect to the position of items during the sequential presentation of two visual shape cues (Inoue & Mikami, 2018). The PFC neurons displayed graded activity with respect to their ordinal position within the sequence and to the visual shapes; e.g. first-ranked items, or second-ranked items. In more complex tasks, PFC neurons were found to fire at particular moments within the sequence (Tanji & Hoshi, 2001); e.g. the beginning, the middle, the end, or even throughout the evolution of the sequence.

Despite these findings, the precise role played by conjunctive cells in the PFC and the mechanisms behind the process are still under investigation. In contrast, the conjunctive cells in the Parietal Cortex have been studied more frequently and many neurocomputational models explain how they contribute to spatial representation (Andersen, Essick, & Siegel, 1985; Andersen & Mountcastle, 1983), coordinate transformation (Andersen, 1997; Pouget & Snyder, 2000) and numerosity capabilities (Hubbard, Piazza, Pinel, & Dehaene, 2005). In most research, conjunctive cells or gain-modulation neurons in Pareto-motor neurons are seen as a way of binding different received information (e.g. in vision and proprioception) for preparing an action (e.g. reaching a target). In Pouget and Snyder (1997, 2000), Pouget proposes that gain-modulated conjunctive cells in the Parietal Cortex can serve as radial basis functions for constructing any spatial metric; e.g., a hand-centered relative metric (Georgopoulos, Merchant, Naselaris, & Amirikian, 2007; Kakei, Hoffman, & Strick, 2003), a head-centered relative metric (Andersen & Mountcastle, 1983). Similar to the role played by conjunctive cells in the spatial domain in the Parietal Cortex, we suggest that the conjunctive cells in the PFC play the role of radial basis functions in the temporal domain to decompose and code sequences. Gain-modulation in the PFC may serve to extract temporal patterns and to represent them as primitives for encoding existing sequences or for generating new ones, see Fig. 1(a–b).

This idea is in line with comparative neuroanatomical studies which attribute similar functions to the parietal cortex and to the prefrontal cortex, representing relative metrics or conjunctive representations (Genovesio, Wise, & Passingham, 2014) such as order with relative duration, and order with relative distance; but only the PFC is in a position to generate goal-based aims in context (Genovesio, Tsujimoto, & Wise, 2009). This is also suggested by Botvinick and Watanabe in Botvinick and Watanabe (2007) that these cells in the PFC describe a compressive representation of sequences without items. Gain-modulated conjunctive cells can give an insight into how the PFC manages to plan sequences and encode them (Dehaene et al., 2015). For instance, they may be seen as a solution to disentangle the features (items) from the sequence (ordinal information) in planning. In line with this idea, they may gate information at particular moments – i.e., not only predicting which action to perform but also knowing *when* to do so within a sequence (Fuster, 2001; Paton & Buonomano, 2018).