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Sameness/difference spiking neural circuit as a relational concept precursor model: A bio-inspired robotic implementation

André Cyr[a,*], Aurore Avarguès-Weber[b], Frédéric Thériault[c]

[a] School of Psychology, University of Ottawa, Canada
[b] Centre de Recherches sur la Cognition Animale, Université de Toulouse, France
[c] Department of Computer Science, Cégep du Vieux Montréal, Canada

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ABSTRACT

This paper presents a bio-inspired virtual and physical robotic model of sameness/difference (SD) abstract relations investigated through associative learning tasks. Considering that the invertebrate bees presumably possess this higher cognitive ability with a relatively tiny brain (Giurfa, Zhang, Jenett, Menzel, & Srinivasan, 2001), an hypothesis of a neural correlate may hold as a minimalist cellular circuit. In order to simulate it, we implemented the model using an artificial spiking neural network (SNN) acting as a robot's brain-controller and a reward-modulated spike-timing dependent plasticity as the learning rule. The model is tested with different operant conditioning procedures of delayed-matching-to-sample and delayed-non-matching-to-sample tasks from dual choices of colors. Apart SD, the color and side simpler associative rules also co-exist. This allows the robot to learn in different scenarios, not knowing the rule to come. Therefore, we showed that depending on its action and the applied reinforcing rules (SD, color or side), the robot dynamically learns any of it, independently and one after the other, all supported by a single SNN. We believe that this SD SNN model could be used as a precursor base to understand and build a generic form of a relational concept mechanism.

Introduction

Relational concepts (RC) are abstract categories defined by associations between perceptual stimuli or events, such as same/different (SD), above/below (Avarguès-Weber, Dyer, & Giurfa, 2010) and more/less among other relations (Doumas, Hummel, & Sandhofer, 2008). Building RC implies the detection of invariant rules between objects, independently of their physical attributes. The same rule should apply for any type of stimuli linked by the appropriate relation. Conceptual learning requires thus a high level of abstraction and has long been thought as a human specific skill that co-evolved with language complexity. Concepts are the cornerstone of human cognition, by being the premise for a non-referential language and mathematical thinking. RC abilities have nevertheless been shown not to be restricted to the human brain but shared to some extent by other large-brained species (Katz, Wright, & Bodily, 2007) as non-human primates (Katz, Wright, & Bachevalier, 2002; Wright & Katz, 2006; Truppa, Mortari, Garofoli, Privitera, & Visalberghi, 2011) or pigeons (Bodily, Katz, & Wright, 2008; Cook & Wasserman, 2007; Zentall, Wasserman, Lazareva, Thompson, & Rattermann, 2008). This sophisticated capacity was unexpectedly demonstrated in the honeybee, an invertebrate that seems to possess the SD cognitive ability (among others RC), despites its relative small brain of 1 million neurons holding in a 1 mm^3 (Avarguès-Weber & Giurfa, 2013; Menzel, 2012; Zhang, 2012). The fact that the miniaturized bee brain can master conceptual learning raises the question of the minimal neural architecture required to allow such a level of abstraction. The bees' performance suggests that RC processing could be supported by relatively simple neural circuits. In this article, our intentions is to pave the way for a neural model of concept learning by addressing the possibility of building a generic model based on simple cellular components to solve "sameness" and "difference" tasks.

Explicit data representation, symbolic and statistical programming represent computational approaches to understand and simulate RC (De Raedt, 2008) with few as embodied implementations (Tenorio-González & Morales, 2016; Van Der Velde, 2016). For example, in the Bentley et al. experiment, they used a hybrid computational method with graph-based and a self-organized map (SOM) to simulate the abstract concept of SD (Bentley, Kurashov, & Lim, 2016). Precisely, a primary SOM extracts the independent visual features of the pictures, feeding a secondary SOM for the

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* Corresponding author.
E-mail addresses: acyr2@uottawa.ca (A. Cyr), aurore.avargues-weber@univ-tlse3.fr (A. Avarguès-Weber), ftheriault@cvm.qc.ca (F. Thériault).

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higher level extraction of the SD rule. Using several learning sets, the mechanism was to incrementally build clusters on the similitude property, then a second-order clustering is made independently of the object feature. The results are projected on a graph and a value distance could be used to meta-organize the new learning set on a scale from “same” to “different”.

Closer to neuroscience, the spiking neural network (SNN) is a connectionist computational method recently used in cognitive modeling, which abstracts the content and the manipulation of knowledge through architectures composed of artificial neural units and synaptic rules (Gerstner & Kistler, 2002; Izhikevich, 2003; Maass, 1997). One major particularity of SNN is the focus on the temporal resolution at the spike level, which gives a precise timing between events. Spike-timing dependent plasticity (STDP) represents one plausible form of encoding those associative relations in synaptic changes (Bi & Poo, 1998; Caporale & Dan, 2008; Markram, Lubke, Frotscher, & Sakmann, 1997). STDP is a directional and causal associative mechanism that biologically explains one type of modification in the neural code, which can also be observed at the behavioral level. Many STDP types exist and some of those require a third factor to engage a synaptic modulation (Frémaux, Sprekeler, & Gerstner, 2010; Pawlak, Wickens, Kirkwood, & Kerr, 2010). Dopamine (Schultz, 1998) in mammals and octopamine (Behrends & Scheiner, 2012; Hammer, 1997; Unoki, Matsumoto, & Mizunami, 2006) in invertebrate species are serious neuromodulator candidates thought to represent a positive reinforcer as third partners implicated in associative learning.

We consider that such SNN could represent a simple neural model level to address the complexity of the SD phenomenon from synaptic changes as explanations to adaptive behavior as experimental measurable observations. We also believe that this SD-SNN model should be tested in the physical world for constraint realism and artificial intelligence objectives. Therefore, we propose a SD model studied from a bio-inspired robotic framework with a SNN. This embodied SD model doesn’t aim to simulate a natural brain structure or fit quantitative data. However, it may contribute to neurobiological research by providing the core for building a generic and functional RC model. Also, since the SD concept is barely explored in the robotic field (Inuzuka, Onda, & Itoh, 1999; Kleyko, Osipov, Björk, Toresson, & Öberg, 2015), proposing such a cognitive function may help to develop robot’s learning skills in complex tasks such as visual categorizations. In both cases, this work on SD has the potential of being reused in other RC types to explain complex incremental adaptive behaviors.

In our experiments, we have decided to evaluate the model using scenarios inspired by the Giurfa et al. honeybees study (Giurfa, Zhang, Jenett, Menzel, & Srinivasan, 2001). In this research, bees in an appetitive context, were first trained to find a sucrose reward on a Y-maze before being individually subjected to a delay-match-to-sample (DMTS) and delay-non-matching-to-sample (DNMTS) tasks. When entering the maze, the bees were shown a sample visual stimulus (e.g. a yellow disc) and had to fly through it by a small hole before entering the decision chamber at the intersection of the two branches of the Y-maze. One branch presented the same visual stimulus as the sample while the other presented a different stimulus (e.g. a blue disc). The bees obtained a reward when choosing according to the “sameness” rule. Another group of bees were trained in a similar design but had to follow the “difference” rule. The sample and the rewarded sides varied from trial to trial preventing the bees to use simpler associative rules. An essential step to conclude on conceptual learning ability was then reached with success when the bees had to transfer the learned relational rule to a novel set of stimuli outside of the training set. Thus, bees trained with visual stimuli were able to transfer with success directly the rule to olfactory stimuli (Giurfa et al., 2001).

Regarding their experiments, we used a similar operant conditioning (OC) procedure to study the SD phenomenon (Avarguès-Weber, Mota, & Giurfa, 2012), linking a visual sensory context, an action and a reinforcer. We adapted the Y-mazes in DMTS and DNMTS tasks, as often used to test conceptual learning capacities in animals (Giurfa et al., 2001) in order to produce the SD generic model (see the methodology section). Briefly, we used a static robot associated with a camera. A pure tone color sample stimulus (green or red) was flashed before a delayed comparison test stimuli, composed of two colors (one color on each side, green or red). Then, the virtual and physical robot had to choose one side and if the response was correct, a reward was applied. Therefore, the SD formation is based on dynamical STDP associative processes, built through trial learning sets. Those sets are represented by the contingency of contextual sample and delayed visual stimuli, the robot’s decision and the reinforcer. Specifically, independent associations are made (increasing the synaptic efficiency) for each trial between the sample, the delayed visual stimuli and the reinforcer when occurring from the chosen action. After few trials, the winning associations emerge from the synaptic weight competition, since they are continuously increased when predicting correctly or decreased when failing to predict the reward of the learning scenario. This competitive process, reinforcing the proper synapses, allows the adequate SD concept to be learned, among any other learning scenario, showing the plasticity of the SNN.

RC implies associative ambiguity as a given stimulus could be either rewarded or not from several coexisting rules. In addition with showing a simple SNN model to solve a SD task, we introduced the rewarding rules on colors and sides as simpler associative rules. This incremental level of complexity was also an objective of this article, enhancing the learning adaptation in neural modeling and robotic contexts. Therefore, the robot had to find the appropriate rule among the three options (one color being constantly rewarded, one side being constantly rewarded, a DMTS/DNMTS scenario) and to be able to switch in an autonomous fashion from one rule to the other. In the next sections, we defined the experimental methodology used in the OC procedures followed by a discussion on the SD and general RC models.

Methodology

Protocol

The virtual experimental design includes a static torso-humanoid robot mounted with a camera (see Fig. 1). In front of it, the colors are shown on a fixed block. First, the robot faces a color picture (red or green), used as the sample stimulus. After a delay of 100 cycles of algorithm (approximately 10 ms per cycle), a test stimulus consisting of a mixed color picture (red on left and green on right or inversely) is then presented (see Fig. 2). Finally, the robot is requested to choose one side of the picture by emitting light from a left or right light-emitting diode (LED) (50 cycles for the decision). The robot is then rewarded depending of its choice from virtually pressing a dedicated button at its back, using infrared sensors. These steps consist of a trial lasting around 500 cycles, which was looped approximately 30 times with a defined inter-trial delay of 250 cycles, randomizing the samples and the tests stimuli. In the absence of a rewarding rule, the robot’s choice stays random. Thus, each simulation is achieved between 6000 and 20,000 cycles depending of the learning scenario, which means that the total simulation time was between one and four minutes. Since a cycle represents the temporal period of a spike in our SNN model, a temporal comparison could be obtained with biological organisms without implying to reflect the real time of the natural parameters. Therefore, our SNN model does not aim

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