Biologically Inspired Cognitive Architectures 23 (2018) 54–63

Contents lists available at ScienceDirect

Biologically Inspired Cognitive Architectures

journal homepage: www.elsevier.com/locate/bica

Research article

# Improving energy consumption of pattern recognition by combining processor-centric and bio-inspired considerations

Yathindu R. Hettiarachchige*, Asad I. Khan, Jan Carlo Barca

*Faculty of IT, Monash University, Melbourne, Australia*

A R T I C L E I N F O

*Keywords:*
Bio-inspired
Distributed pattern recognition
Parallelism
Strong AI

A B S T R A C T

This paper investigates aspects of bio-inspired models that help create more energy efficient methods in pattern recognition. A comparison between a biologically plausible pattern recognition approach and a purely computer based (algorithmic) approach yielded three main findings. Firstly, the occurrence of low-complexity parallel sub-processes within the bio-inspired approach allows higher energy efficiency by relaxing the requirement of having faster processors. Secondly, the bio-inspired approach takes advantage of numerous computationally inexpensive sub-processes that will scale better in massively parallel environments, such as neuromorphic computers, thus providing comparable speed. Finally, it is far more easier to adapt across a range of application domains than its algorithmic counterpart.

## Introduction

Small insects such as honey bees have been shown to be able to recognize human faces (Dyer, Neumeyer, & Chittka, 2005) and even form abstract concepts (Avarguès-Weber, Dyer, Combe, & Giurfa, 2012; Giurfa, Zhang, Jenett, Menzel, & Srinivasan, 2001) all using their miniature brains running on a fraction of the energy consumed by a microprocessor. Conversely, attempts to implement brain like functions in software lead to an exponential increase in computational complexity and in turn energy consumption. In this paper we combine core aspects of bio-inspired and computer-centric approaches with parallelism for facilitating artificial general intelligence.

Bio-inspired approaches apply higher level concepts from neurobiology to solve large and complex problems. The *algorithmic* approaches attempt to solve these problems based solely on Von Neumann architectural considerations. The results of our work illustrate that applying key neurobiological principles with strong *algorithmic* considerations, will derive the best computer-based intelligence.

A human brain consumes between 14 W and 16 W approximately.[1] To put these values in perspective the power consumption of a conventional GPU is about 119 W (McLaughlin, Riedy, & Bader, 2014).[2] With this energy constraint in mind consider various complex tasks a brain performs with reasonable speed and precision, often in parallel with memorization/recall, pattern recognition and prediction, sensory inputs, and motor functions. However, also note that implementing brain-like computations using the bio-inspired approach generally incur a significant loss in run-time efficiency and accuracy. At times we find that algorithms written specifically for the machine domain perform significantly better than their bio-inspired alternatives in terms of speed and accuracy. Why we experience this loss in overall effectiveness and more importantly, how we can better devise intelligent systems (from these observations) form the main premises of this paper.

It is evident that biological brains have arrived at some optimal compromise between speed, accuracy, energy efficiency, and adaptability. Approaches such as neuromorphic computing seem to be converging upon such a compromise. However, neuromorphic computing would require an overhaul of current software engineering infrastructure. In this paper we compare a strongly bio-inspired approach with an algorithmic approach for object detection. Through this comparison, we arrive at the following conclusions:

- Bio-inspired approaches take advantage of lightly-coupled, and computationally inexpensive sub-processes, which can be executed in a massively parallel manner.
- The ensuing parallelism may be exploited to devise more power efficient parallel systems comprising lower speed processors.
- Massive parallelism in neurobiological functions, and often manifested by the bio-inspired approach, is very likely to be an important

* Corresponding author.
*E-mail addresses:* yathindu.hettiarachchige@monash.edu (Y.R. Hettiarachchige), asad.khan@monash.edu (A.I. Khan), jan.barca@monash.edu (J.C. Barca).

[1] The brain uses approximately 20% of the resting metabolism (Attwell & Laughlin, 2001). Average male and female basal metabolic rates are 7100 kJ and 5900 kJ respectively (Victoria).

[2] 119 W is the result of averaging the values reported in Table 3 in McLaughlin et al. (2014).

https://doi.org/10.1016/j.bica.2018.01.004
Received 31 March 2017; Received in revised form 10 January 2018; Accepted 12 January 2018
2212-683X/ 

enabler of low-energy computations.

This paper is organized as follows: Section 'Background Literature' presents an overview of the literature that informs the contribution of this paper. Sections 'Map seeking circuits' and 'Phase Based Tracker' describe the two approaches we have selected for comparison. Section 'Comparison of bio-inspired and algorithmic approaches' contains our main contributions, analysing the two approaches in terms of speed, accuracy, energy efficiency and generalisability. Finally Section 'Conclusions and Remarks' concludes the paper with a discussion of future work.

## Background literature

### *Sparse-coding*

Sparse-coding as an important mechanism in the sensory processing of the brain is supported by evidence from a variety of experimental studies on an assortment of species. Olshausen and Field (2004) describe the theory and supporting evidence very clearly and tersely. Sparse-coding is an idea that is mainly associated with sensory information processing in animals. The crux of this idea is that out of large populations of neurons only a relatively low number of neurons would represent a particular piece of sensory information. A good example is that a neuron in the retina responds to any contrast while a neuron in the cortex responds to a particular edge orientation (Olshausen & Field, 2004). This example also demonstrates that information is represented more sparsely as it is transmitted further down the processing chain.

Sparse-coding appears to be a fundamental mechanism for processing sensory information in the brain as it has experimentally been shown to be utilized in visual, auditory, olfactory and somatosensory systems, across several different species such as: the visual system of macaques (Vinje & Gallant, 2002), the auditory cortex of rats (DeWeese, Wehr, & Zador, 2003), the somatosensory system of rats (Brecht & Sakmann, 2002) and the olfactory system of insects (Perez-Orive et al., 2002). Sparse-coding improves memory capacity, biological evidence to support this has only been discovered recently. In their study on sparse odor coding in fruit flies Lin, Bygrave, de Calignon, Lee, and Miesenböck (2014) show that disrupting a particular feedback loop decreases the sparsity of neuron responses and also inhibits the discrimination of similar but not dissimilar odors (Lin et al., 2014). This finding supports the theory of Sparse Distributed Memories, as we will explain in the next section.

### *Sparse Distributed Memories*

Sparse-coding research is complemented by Kanerva's Sparse Distributed Memories (SDMs) (Kanerva, 1988). SDMs were developed as a mathematical model for long term memory. SDMs take advantage of the statistical properties of high dimensional (HD) binary spaces. Each point in a HD space is addressed by a HD vector. The "sparse" in "Sparse Distributed Memories" comes from the fact that information is encoded into this HD vector sparsely such that the vector mostly contains zero values. Owing to the high number of dimensions, any single point within a HD space would be relatively far from other unrelated points. In fact if two points were drawn randomly from such a space they are likely to be orthogonal. This also means that information can be encoded into the HD vector somewhat imprecisely and that an accidental overlap is highly unlikely. Features like imprecise information encoding make SDM a biologically plausible model for memory. For example the retina is very unlikely to receive the same inputs twice yet we are capable of identifying specific objects.

### *Vector Symbolic Architectures*

A set of ideas very closely related to SDMs, that also utilize HD vectors, have been given the umbrella term Vector Symbolic Architectures (VSAs) (Gayler, 2004; Kanerva, 2014; Levy & Gayler, 2008; Osipov, Khan, & Amin, 2014). VSAs primarily aim to model cognition, random binary HD vectors are used to represent concepts and vector operations such as addition and multiplication are used to compose lower level concepts into higher level concepts and form relationships between concepts. All VSAs are based on vectors and operations are carried out on vectors, hence the VSA operations are inherently parallel. Several different approaches have been proposed for computing the VSAs. Binary Spatter Codes (BSC) (Kanerva, 1994), Holographic Reduced Representations (HRR) (Plate, 1995) and MAP (Multiply, Add, Permute) Coding (Gayler, 2004). The main differences between these approaches are the values of the HD vectors and specific operations used. For example, HRRs appear to be fairly different in comparison with MAP and BSC, since HRRs utilize real valued vectors instead of binary vectors.

### *Liquid State Machines*

Liquid State Machines (LSMs) are an accepted model for brain-like computations (Maass, Natschläger, & Markram, 2002). LSMs offer a computational model which does not require a central "clock", lending itself to algorithms with high levels of parallelism. An analogy Maass et al. (2002) use to explain the approach is a puddle of water. External influences can cause perturbations within the puddle, which in time weaken and disappear. At any point in time the state of the perturbed liquid encodes present and past states, this coupled with the attenuation of perturbations can be thought of as a fading memory. In LSM, inputs generate perturbations which are used to map the desired output to the input.

### *Deep learning*

VSAs and Deep learning share high levels of similarities. Both approaches are inspired by biological sparse-coding and both attempt to reduce complexity by using hierarchical compositions of low level components to form high level components. However a key difference is that deep learning algorithms such as Convolutional Neural Networks (ConvNets) (LeCun, Kavukcuoglu, & Farabet, 2010) automatically learn good internal representations. ConvNets have been widely adopted by the computer vision community because they have produced very good results in object recognition tasks (Krizhevsky, Sutskever, & Hinton, 2012).

While these advancements are substantial, when we look at what biological vision appears to be capable of, the current state-of-the-art in computer vision appears to only capture a narrow slice of this functionality. Lewicki, Olshausen, Surlykke, and Moss (2014) focus scene analysis in natural environments and argue that the problem of recognition has been defined too narrowly. Indeed much of the attention in computer vision has been to develop systems capable of assigning labels to pixels. But labels do not capture enough information to account for natural behaviour. Lewicki et al. cite the fact that many behaviours require the organism to have knowledge of things such as the object's 3D pose, location and geometric shape. Lewicki et al. go on to argue that treating recognition as a categorization problem causes the issue of representation to go unaddressed. They make the case that recognition in animals likely uses some representation that encodes a 3D object structure into a viewpoint invariant form. They point out that current research that uses 3D models represent the 3D models in Euclidean space which is unlikely in nature. In the next section we describe a little known algorithm that addresses some of Lewicki et al. criticisms.