Neurocomputing 138 (2014) 3–13

Contents lists available at ScienceDirect

Neurocomputing

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

A brain-inspired spiking neural network model with temporal encoding and learning

Qiang Yu [a], Huajin Tang [b,c,*], Kay Chen Tan [a], Haoyong Yu [d]

[a] Department of Electrical and Computer Engineering, National University of Singapore, 117576, Singapore
[b] Institute for Infocomm Research, Agency for Science Technology and Research (A*STAR), 138632, Singapore
[c] College of Computer Science, Sichuan University, Chengdu 610065, China
[d] Department of Bioengineering, National University of Singapore, 117576, Singapore

ARTICLE INFO

Article history:
Received 21 August 2012
Received in revised form
18 March 2013
Accepted 27 June 2013
Available online 25 March 2014

Keywords:
Spiking neural networks (SNNs)
Pattern recognition
Cognitive memory
Temporal encoding
Temporal learning

ABSTRACT

Neural coding and learning are important components in cognitive memory system, by processing the sensory inputs and distinguishing different patterns to allow for higher level brain functions such as memory storage and retrieval. Benefitting from biological relevance, this paper presents a spiking neural network of leaky integrate-and-fire (LIF) neurons for pattern recognition. A biologically plausible supervised synaptic learning rule is used so that neurons can efficiently make a decision. The whole system contains encoding, learning and readout. Utilizing the temporal coding and learning, networks of spiking neurons can effectively and efficiently perform various classification tasks. It can classify complex patterns of activities stored in a vector, as well as the real-world stimuli. Our approach is also benchmarked on the nonlinearly separable Iris dataset. The proposed approach achieves a good generalization, with a classification accuracy of 99.63% for training and 92.55% for testing. In addition, the trained networks demonstrate that the temporal coding is a viable means for fast neural information processing.

1. Introduction

The great computational power of biological systems has drawn increasing attention from researchers. Although the detailed information processing involved in memory is still unclear, observed biological processes have inspired many computational models operating at power efficiencies close to biological systems. Pattern recognition is the ability to identify objects in the environment, and several conventional methods are used to implement it, such as maximum entropy classifier, naive Bayes classifier, decision trees, and support vector machines. As is a necessary first step in all cognitive processes including memory, it is better to consider pattern recognition from brain-inspired models which could potentially provide great computational power.

To approach biological neural networks, the artificial neural networks (ANNs) are developed as simplified approximations in terms of structure and function. Since early neurons of the McCulloch–Pitt neuron in 1940s and the perceptron in 1950s [1], referred as the first generation neuron models, ANNs have been evolving towards more neural-realistic models. Different from the first generation neurons in which step-function threshold is used, the second generation neurons use continuous activation functions (like a sigmoid or radial basis function) as threshold for output determination [2]. The first two generations are referred as traditional neuron models. Studies on biological systems disclose that neurons communicate with each other through action potentials (pulses or spikes). As the third generation neuron model, spiking neurons raise the level of biological realism by utilizing spikes. The spiking neurons dealing with precise timing spikes improve the traditional neural models on both the aspects of accuracy and computational power [3]. There are several kinds of spiking neuron models such as the integrate-and-fire (IF) model [4], the resonate-and-fire model [5], the Hodgkin–Huxley model [6], and the Izhikevich model [7]. Since the IF model is simple and computationally effective [8], it is the most widely used spiking neuron model [9–15], despite other more biologically realistic models.

Encoding is the first step in creating a memory, which considers how information is represented in the brain. Although results remains unclear, there are strong reasons to believe that it is optimal using pulses to encode the information for transmission [16]. The inputs to a spiking neuron are discrete spike times. Rate coding and temporal coding are two basic and widely studied schemes of encoding information in these spikes. In the rate coding the average firing rate within a time window is considered, while for the temporal coding the precise timings of spikes are considered [17]. Neurons, in the retina [18,19], the lateral

* Corresponding author.

http://dx.doi.org/10.1016/j.neucom.2013.06.052
0925-2312/

geniculate nucleus (LGN) [20] and the visual cortex [21] as well as in many other sensory systems, are observed to precisely respond to stimuli on a millisecond timescale [22]. Temporal patterns can carry more information than rate-based patterns [23–25]. A simple example of the temporal encoding is spike latency coding. The capability of encoding information in the timing of single spikes to compute and learn realistic data is demonstrated in [26]. Since this coding utilizes only single spikes to transfer information, it could potentially be beneficial for efficient pulse-stream very large scale integration (VLSI) implementations.

Many algorithms for spiking neural networks (SNNs) have been proposed. Based on arithmetic calculations, the SpikeProp [9,26] was proposed for training SNNs, similar in concept to the back-propagation (BP) algorithm developed for traditional neural networks [27]. Others use bio-inspired algorithms, such as spike timing dependent plasticity (STDP) [28–31], the spike-driven synaptic plasticity [13], and the tempotron rule [14]. Although the arithmetic calculations can easily reveal why and how networks can be trained, the arithmetic-based rules are not a good choice building networks with a biological performance. STDP is found to be able to learn distinct patterns in an unsupervised way [12], and it characterizes synaptic changes solely in terms of the temporal contiguity of presynaptic spikes and postsynaptic potentials or spikes. In the spike-driven synaptic plasticity [13], a rate coding is used. The learning process is supervised and stochastic, in which a teacher signal steers the output neuron to a desired firing rate. Being different with spike-driven synaptic plasticity, the tempotron learning rule [14] is efficient to learn spiking patterns where information is embedded in precise timing spikes.

Although SNNs show promising capability in playing a similar performance as living brains due to their more faithful similarity to biological neural networks, the big challenge of dealing with SNNs is reading data into and out of them, which requires proper encoding and decoding methods [32]. Some existing SNNs for pattern recognition (as in [13,33]) based on the rate coding. Different from these SNNs, we focus more on the temporal coding which could potentially carry the same information efficiently using less number of spikes than the rate coding. This could largely facilitate the computing speed.

In this paper, we build a bio-inspired model of SNNs containing encoding, learning and readout. Neural coding and learning are the main considerations in this paper, since they are important components in cognitive memory system by processing the sensory inputs and distinguishing different patterns to allow for higher level brain functions such as memory storage and retrieval [34]. Inspired by the local receptive fields of biological neurons, the encoding neuron integrates information from its receptive field and represents the encoded information through precise timing of spikes. The timing scale of spikes is on a millisecond level which is consistent with biological experimental observations. The readout part uses a simple binary presentation as proposed in this paper to represent fired or non-fired state of the output neuron. Through the encoding and readout, SNNs can be applied to deal with real data well.

The main contribution of this paper lies in the approaches of designing SNNs for pattern recognition. Pattern recognition helps to identify and sort information for further processing in brain systems. A new coming pattern is recognized upon paying attention and similarity to previously learned patterns which are obtained through weight modification. Recognition memory is formed and stored in synaptic strengths. Inspired by biology, spiking neurons are employed for computation in this paper. This paper is extended from our preliminary work [35] by adding more comparative and analytic studies. The system contains encoding, learning and readout part. We demonstrate that, utilizing the temporal coding and learning, networks of spiking neurons can effectively and efficiently perform various classification tasks. In addition, the results also demonstrate that the temporal coding is a viable means for fast neural information processing and learning on real-world data.

The rest of this paper is organized as follows. Section 2 presents the architecture of the spiking neural network. Section 3 describes the temporal learning rule we used in our approaches. The relationship between this rule and well-studied STDP is also introduced. Section 4 shows the ability of the network to learn different patterns of neural activities (discrete-valued vectors). Section 5 shows the SNN for learning continuous input variables. We use the well-known Iris dataset problem to benchmark our approach against several existing methods. In Section 6, we demonstrate the ability of our spiking network for learning real-world stimuli (images). Finally, we end up with discussions in Section 7, followed by conclusions in the last section.

2. The spiking neural network

In this section, we describe the whole system architecture of spiking neurons for obtaining recognition memory. The system composes 3 functional parts: the encoding part, the learning part and the readout part (see Fig. 1). A stimulus consists of several components. The components are partially connected to encoding neurons to generate encoded spiking information. The encoding neurons are fully connected to learning neurons.

Each part plays a different functional role in the system: the encoding layer generates a set of specific activity patterns that represent various attributes of external stimuli; the learning layer tunes the neurons' weights making sure that particular neurons can respond to certain patterns correctly; the readout part extracts information about the stimulus from a given neural response. Through this architecture, the problem of getting data into and out of the spiking neural network is solved, and the task of pattern recognition could be fulfilled.

2.1. Encoding

The encoding part aims to generate spiking patterns that represent the input stimuli. The temporal encoding is used over rate-based encoding when patterns within the encoding window [17] provide information about the stimulus that cannot be obtained from spike count. The latency code [17] is a simple example of temporal encoding. It encodes information in the timing of response relative to the encoding window, which is usually defined with respect to stimulus onset. The single spike latencies are used to encode stimulus information in our system. Within the encoding window, each input neuron fires only once.

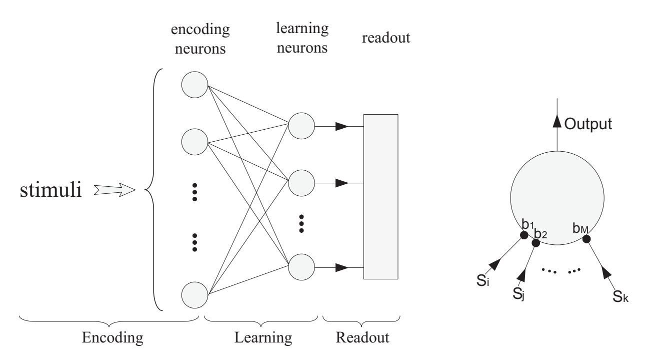

Fig. 1. Architecture for pattern recognition. Left: a schematic of the system architecture. Right: encoding neuron model. It has M input points connected to part of the stimulus and one output. It performs a mapping function that converts a value string to a temporal spike.