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Wavelet decomposition and phase encoding of temporal signals using spiking neurons

Zhenzhong Wang, Lilin Guo, Malek Adjouadi *

Center for Advanced Technology and Education, Florida International University, 10555 West Flagler Street, EC 2220, Miami, FL 33174, USA

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ABSTRACT

Spike encoding is the initial yet crucial step for any application domain of Artificial Spiking Neural Networks (ASNN). However, current encoding methods are not suitable to process complex temporal signal. Motivated by the modulation relationship found between afferent synaptic currents in biological neurons, this study proposes a spike phase encoding method for ASNN, which could perform wavelet decomposition on the input signal, and encode the wavelet spectrum into synchronized output spike trains. The spike delays in each synchronizing period represent the spectrum amplitudes. The encoding method was tested in two implementation examples: (a) encoding of human voice records for speech recognition propose; and (b) encoding of multichannel electroencephalography (EEG) records with the aim to detect interictal spikes in patients with epilepsy. Empirical evaluations confirm that encoded spike trains constitute a good representation of the continuous wavelet transform of the original signal, with the ability to capture interesting features from the input signal.

1. Introduction

The most significant difference between Artificial Spiking Neural Networks (ASNN) and traditional neural networks is that information in ASNN is represented by spike trains which are a series of pulses with timings of interests. There are mainly two kinds of interpretations developed in signal processing applications about how information is related to spike trains: (1) the rate encoding, which assumes that the information is encoded by the counts of spikes in a short time window; and (2) the spike time encoding which considers information carried at the exact time of each pulse in the spike train. Although the mechanisms for data representation and analysis using biologically-inspired neural networks is still under development, empirical evidence has shown that spike time encoding might be more reliable in explaining experiments on the biology of nervous systems [1,2].

Both rate encoding and spike time encoding essential in ASNN applications. The easiest way to rate encode an analog signal is to feed it to a Poisson neuron, which fires output spikes at probability proportional to its membrane potential, thus making its firing rate within a short time window proportional to the amplitude of the input signal. Such an encoding method has been adopted by Sprekeler et al. [3] and Keer et al. [4] in order to analyze the recurrent ASNN behaviors. Although Poisson neuron model is simple and suitable for theoretical analysis, it was rarely implemented in real-world applications due to its inaccuracy in mapping analog signals to spike trains. De Garis et al. [5] introduced another rate encoding method which deconvolves the input signal into its individual spike responses, so that the post-synaptic potential of the encoded spike train could be quite similar to the original signal. Schrauwen and Van Campenhout [6] improved algorithm proposed by De Garis et al. by optimizing the deconvolution threshold yielding the so-called Bens Spiker Algorithm (BSA). BSA has been used widely as a rate encoding method for ASNN applications [7–9]. The major problem of this type of rate encoding is that an averaging time window is required for each sampling of the input signal, which as a consequence limits the temporal resolution of the encoded signals.

In order to overcome this drawback, receptive fields are introduced by other researchers to improve the temporal resolution [10,11], where input signals are first decomposed by Gaussian windows with variant shifts of the window center, and then fed to an array of neurons which convert them to multiple spike trains. Address-Event Representation (AER) is an asynchronous protocol designed for analog neural system simulation platforms [12]. However, AER is also referred to as an encoding method by other groups of researchers [13–15]. When used as an encoding method, encounters of “ON” and “OFF” events in the input signals are registered by AER to generate corresponding output spikes. The “ON” and “OFF” events in AER indicate the time when a change in the input signal either exceeds a positive threshold or fall behind a negative threshold. Under such definition, AER could be treated as a rate encoding method with regards to the derivatives of the input signal.

* Corresponding author. Tel.: +1 305 348 4106.
E-mail address: adjouadi@fiu.edu (M. Adjouadi).

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Synchronized spike time encoding, dubbed as Phase Encoding (PE), was also widely used in ASNN application. A simple implementation of PE could be realized by linearly mapping the input signal to the delay of spikes within each synchronizing period [16]. This implementation of PE requires the input signal either to be static or vary at frequencies much lower than the synchronizing frequency. Temporal receptive fields could also be utilized for PE to improve the encoding resolution [17,18]. To be more biologically plausible, Rumbell et al. [19] introduced a synchronizing method which considered spiking neurons as PE units instead of performing linear mapping between analog values and spike delays. Receptive fields in this study were applied to the amplitude dimension instead of the temporal dimension, which yielded good performance for static input data. However, PE method which could accurately encode temporal signals is still under development.

Beside receptive fields, wavelet transform is another useful approach to pre-process input signals before encoding them into spike trains. Wavelet transform is commonly used as a preprocessing method for using ASNN for image classification [20,21] or computer vision tasks [22,23]. The generated wavelet coefficients are in general much less variable than the raw signals, which makes it easier for rating or phase encoding the coefficients into spike trains. However, current encoding schemes for ASNN which incorporates wavelet transform all apply wavelet decompositions off-line, and operates outside the ASNN platform, which makes the encoding scheme inefficient for encoding prolonged temporal signals.

In this paper, we propose a preprocessing unit for the Leaky Integrate-and-Fire (LIF) spiking neurons. The assumption is that an encoding device combining the preprocessing unit with a LIF neuron could be used to encode analog signals with wide frequency range. We will demonstrate in Section 2 that our preprocessing unit could decompose the input signal into wavelet spectrum, and further encode the spectrum amplitude into the delay amount between output spikes and the clock signals. Empirical results of PE encoding of two different types of signals (speech and EEG signals) are provided in Section 2.5, with linearity, temporal resolution issues and possible extension of the encoding method discussed.

2. Methods

In this section, we will demonstrate that an array of specially designed encoding devices could perform wavelet decomposition of temporal signals. We purposely designed the encoding device by incorporating a two-stage spike triggered modulate-and-integrate module with traditional LIF neurons, and made such pre-processing module compatible with ASNN platform, so that the encoding device is easy to implement on any ASNN platforms. Inspired by the multiplication relationship found among afferent synaptic currents in biological neurons [24], we found that delay synchronized spikes sent to the two synapses integrated in the special designed LIF neuron could trigger the wavelet transform of the input signal at certain time scales, and encode the spectrum amplitudes into delays between the output fire times and the control spike arriving times. Simulations in this research were conducted using NEural Simulation Tool [25] (NEST) with the encoding device implement and integrate into the simulation kernels.

2.1. LIF encoding

Spiking neuron models are typically a set of Ordinary Differential Equations (ODE) which attempt to capture the dynamics of the neuron membrane potential. Different neuron models have been proposed by researchers to mimic the electrical behaviors of biological neurons. Among these neuron models, LIF model was believed to be a reasonable simplification of biological neuron with balanced accuracy and efficiency. LIF spiking neuron is described by one-dimensional ODE using the following equations:

$$\tau\frac{du(t)}{dt} = -u(t) + \frac{\tau}{C_m}I_{all}(t) \tag{1}$$

where u is the membrane potential, τ and C_m are the time constant and capacitance of the neuron, respectively, with I_{all} defining the overall afferent current. The firing condition and post-fire behavior of the LIF neuron in (1) can be defined by the following equation:

$$\text{if } u = u_{th} \quad \text{and} \quad \frac{du(t)}{dt} > 0, \quad u \leftarrow u_c \tag{2}$$

where u_{th} is the firing threshold and u_c is the post-fire resetting potential. Note that a derivative condition is applied to the firing conditions in the same manner as in Wang et al. [26]. Such derivative condition ensures that the neuron only fires when its membrane potential in an upward trend crosses the threshold, a condition which is thus set to avoid accidental fires if the resting potential of the neuron is higher than its firing threshold.

The stimulation to LIF neuron is typically assumed to be a summation of all weighted synaptic currents and an external current:

$$I_{all}(t) = I_e(t) + \sum_j w_j I_s(t - s_j) \tag{3}$$

In this equation, $I_e(t)$ is the external current, $I_s(t)$ is the shape function of the post-synaptic current (PSC), s_j is the time that the j-th spike arrives at the synapse, and w_j is the connection efficacy corresponding to the j-th input spike.

Consider a quasi-static input signal being used as the external current to the LIF neuron, and no synaptic stimulation was connected, (1) could be solved as

$$u(t) = u_c \exp\left(-\frac{t - t^f}{\tau}\right) + \tau I_e(t)\left[1 - \exp\left(-\frac{t - t^f}{\tau}\right)\right] / C_m \tag{4}$$

where t^f is the most recent fire time of the LIF neuron. The output spike interval T is thus a function of I_e as defined below

$$T = \tau \ln\left(\frac{u_c C_m - \tau I_e}{u_{th} C_m - \tau I_e}\right) \tag{5}$$

Since the reset potential is usually lower than the threshold u_{th}, larger I_e yields shorter spike interval and thus higher firing rate over a short time window. The input signal is rate encoded in this configuration.

Rumbell et al. [19] suggested a method to generate phase encoded spike train using LIF neurons. A global inhibitory neuron has been connected to all encoding neurons, so that the reset times of these neurons are synchronized, and the firing time interval found in (5) could be converted into the firing delays between neurons.

Encoding methods using LIF neurons however suffer from one major drawback in that the input signal should be quasi-static in comparison to the time constant of the LIF neuron. Although temporal decomposition methods such as Gaussian receptors could reduce the fluctuation of the input signal, the number of receptors increase dramatically with increasing frequency of the input signal, which prevents the encoding method from capturing fast transients in the input signals.

2.2. Spike triggered modulation

Although linear summation of synaptic currents and external current as performed in (3) has been widely accepted as a simplified relationship among the afferent stimulations in large scale ASNN, the interaction between post-synaptic currents was found to be more complicated in biological nervous system. Koch and Segev [24] found that biological neurons might approximate sum

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