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Rate Coding vs. Temporal Coding – Is Optimum Between?

Mikhail Kiselev

Department of Mathematics and Information Technologies
Chuvash State University
Cheboxary, Russia
mkiselev@megaputer.ru

Abstract—In this paper, we consider a novel approach to information representation in spiking neural networks. In a certain sense it is a combination of two well-known coding schemes – rate coding and temporal coding. Namely, it is based on asynchronous activity of ensembles of polychronous neuronal groups – groups of neurons firing in determined order with strictly fixed relative temporal delays. We demonstrate how a rate-coded input signal may be converted into this representation form by network structures which are formed as a result of network self-organization process based on STDP-style synaptic plasticity.

Keywords—*spiking neural network; polychronization; STDP; rate coding; temporal coding; chaotic network; network self-organization*

I. INTRODUCTION

Neurons in spiking neural networks (SNN), which are the most plausible models of biological neuron ensembles, exchange short pulses, called spikes. It is postulated in the majority of SNN models that all spikes have the same form and amplitude (although, alternative opinions exist – [1]). Therefore, a single spike can hardly be considered as an information unit – information is encoded as some properties of the sets of spikes. Many encoding methods have been explored but they can be divided into 2 large groups (see an interesting discussion on their interrelation in [2]). The first group uses the mean firing frequency measured within a certain time window for one or several neurons as an informational parameter. The exact firing time of an individual neuron is not significant in this approach – in this sense it can be called asynchronous. But the exact neuron firing times play an important role in the second group – for that reason these coding methods are generally called temporal coding. One of the well-studied variants of temporal coding is based on the concept of polychronous neuronal groups (PNG) [3]. In this approach, presence of some discrete property, appearance of certain stimulus and so on is represented as the activity of a neuronal group specific for this stimulus so that the relative firing times of all neurons in this group are strictly fixed. There is experimental evidence that the temporal coding is really used for information representation and processing in the brain cortex [4, 5] (while asynchronous coding is utilized mainly in the peripheral nervous system). The PNG-based coding scheme has a number of advantages, for example, a huge potential informational capacity. As it was noted in [3], even the same

set of neurons can encode a great number of different stimuli using neuron firing order and length of inter-spike intervals unique for each stimulus. This coding method is noise-resistant. It can serve as a natural basis for the working memory mechanism [6]. But it does not provide a natural way to code continuous values. In the asynchronous approach, the evident parameter representing stimulus strength is mean firing frequency (rate coding). Another problem is lack of understanding how a temporally encoded signal appears from asynchronous sources. For example, the well-known work [6] demonstrates how PNGs storing information about recent stimuli arise in the chaotic SNN. However, these stimuli were already represented as sequences of spikes strictly fixed in time (this is also true for a more recent research on SNN training [7, 8]). For this reason, it would be important to understand what kind of SNN structures could implement re-coding the asynchronous signal – at least because most primary sensory signals seem to be represented in the rate-coded form. Nevertheless, works considering this kind of conversion remain surprisingly few. For example, a possible role of ensembles of hippocampal pyramidal neurons in this process was considered in [9]. A general approach to the solution of this problem based on PNGs, which exist or spontaneously emerge in a chaotic neural network, was presented by Eugene Izhikevich in [3]. However, neither this work, nor the subsequent works devoted to polychronization did not either consider, to the extent of my knowledge, the concrete conditions under which this conversion could be realized, or report an experimental evidence for its realization. An attempt to find a solution to this problem was made by me in my recent article [10]. It was demonstrated in this work, that conversion between these two coding schemes could be performed under certain conditions by a homogenous chaotic neural network. However, definitions of PNG and temporal coding used there differed strongly from their original definitions. The concept of PNG proposed by Izhikevich suggested that PNG activation triggered by appearance of a certain stimulus involves all or almost all the neurons in the group which fire with the pre-defined delays one after one. The possible absence of few spikes in this sequence is admitted as a noise tolerance measure. However, in [10] PNG response to stimulus was expressed in the activity of the third part of its neurons, at most, – so that reactions to the same pattern might imply activities of completely different PNG subsets. And further research did not show any ways to improve this result. Although, from formal point of view, PNG activity in [10]

really contains information about stimuli presented, it is hardly possible to use this information for further processing.

The solution proposed in the present paper is based on a novel form of information coding in SNN, which is a combination, in a certain sense, of asynchronous and polychronous coding (so we will call it *A/P-coding*) and inherits advantages of both. Namely, a structure realizing this coding scheme (to be referred to as *A/P-recognizer*) is not one big PNG but an ensemble of smaller PNGs. Indicator of certain stimulus or property is activation of some threshold number of PNGs from this ensemble. It is required that this threshold number should not be much less than the ensemble size. Here, we say that PNG is active only if **all** its neurons fire at the prescribed moments of time. But activations of PNGs in the ensemble can be completely asynchronous with respect to each other – in any order and with any time shifts. In contrast with temporal coding based on a single PNG, this approach permits encoding stimulus strength or value of an attribute as a number of active PNGs in the ensemble. Comparing it with [10], it could be said that we let different parts of the big PNG be asynchronous and thus achieve a greater degree of activation of the whole structure making stimulus representation more stable. At the same time, advantages of PNG-based coding are retained – as before, the same group of neurons can correspond to many different PNGs and participate in coding many features.

Further material is organized in the following way. Since our main method is computer simulation, we describe used models of neurons and network, simulation of rate-coded input signal. Further, we present an algorithm to find A/P-recognizers in SNN and a procedure to create a network producing good A/P-recognizers. Result evaluation, discussion, and some plans for the development of this research are included in the final part of the paper.

II. THE NEURONS AND THE NETWORK

We use the simplest functional model of a neuron – a leaky integrate-and-fire (LIF) neuron [11]. The membrane potential u is rescaled so the rest potential value equals 0, while potential threshold value necessary for a neuron to fire equals 1. The excitatory synapse model is current-based, inhibitory synapses are conductance-based. The simplest “instantaneous” synapse model (delta-synapse) is utilized in which the presynaptic spike effect on membrane potential proportional to synapse weight is instantaneous and has zero duration. Thus, presynaptic spike coming to an excitatory synapse with the weight w_i increments u by w_i while the spike coming to an inhibitory synapse with the weight w_a decrease u by the value $(u - E_I)(1 - \exp(-w_a))$, where E_I is inhibitory reversal potential. Besides that, u permanently decays with the time constant τ . If the membrane potential reaches value 1 as a result of incoming excitatory spike, the neuron fires, the potential is reset to 0 and neuron becomes unable to fire again during the time interval τ_R .

Spikes propagate from neuron to neuron with non-zero delays. Distribution of values of these delays plays a crucial role. It was noted in [10] that the maximum number of potential PNGs exists in the networks where neurons are not placed chaotically, but form a certain spatial order. In our

model, synaptic delays between excitatory neurons are selected as if the neurons were randomly scattered on a sphere and delays were proportional to the distance between neurons (the maximum delay equals 30 ms). All connections of inhibitory neurons are very fast – 1 ms. In all other senses, network is absolutely chaotic – for example, the probability that two given neurons are connected depends only on their types (excitatory or inhibitory).

Excitatory synapses are plastic. The plasticity model is based on STDP [11]. However, it is known that in recurrent SNNs STDP easily leads to instability – active closed circuits of excitatory neurons grow and become more and more active due to unlimited growth of weights of their connections caused by STDP. As a result, the constant activity of these circuits may suppress completely all other network activity. In order to prevent this negative scenario of network development we introduce a homeostatic amendment to the standard STDP model. Namely, value of long-term synaptic potentiation (LTP) depends on neuron activity. Very active neurons lose ability to strengthen their synapses. Virtually, we introduce a stabilizing negative feedback in the STDP law. It is realized by introducing the new variable η as a part of neuron state. It equals 1 after a long period of quiescence. When a neuron fires, η is decreased by $\Delta\eta^-$. After that it grows with the constant speed $\Delta\eta^+$ until reaches 1 again. Synaptic weights are limited by the values w_{\min} and w_{\max} because the plasticity law is applied to the value of the so called *synaptic resource* W [12] instead of the weight itself. The relationship between these two variables is expressed by the equation

$$w = w_{\min} + \frac{(w_{\max} - w_{\min}) \max(W, 0)}{w_{\max} - w_{\min} + \max(W, 0)}, \quad (1)$$

so when W runs from $-\infty$ to $+\infty$, w runs from w_{\min} to w_{\max} . In the starting network state weights of all connections of the same type were initialized by the same values, but due to synaptic plasticity excitatory weights scattered in the range $[w_{\min}, w_{\max})$ thus providing the network with some intrinsic structure.

III. THE RATE-CODED INPUT SIGNAL

At last, let us consider the input signal which we would like to convert. Our model contains special nodes which serve as sources of external signal. The excitatory and inhibitory neurons are connected to these *input nodes* via excitatory synapses. The input nodes are a source of a mix of two spike streams – *noise* and *patterns*. Noise component is simulated by random generation of spikes with a certain constant mean frequency. Each pattern corresponds to some subset of input nodes. These subsets are of the same size and may intersect. Regularly, with 200 ms period, spike frequency on one of these subsets becomes very high (300 Hz). These high frequency episodes are short (30 ms). Order of the patterns is selected randomly. It is a typical example of a rate-coded signal. The stimulus is expressed by the elevated mean spike frequency while the exact position of individual spikes is insignificant.

IV. A/P-CONVERTER (OR RECOGNIZER)

In fact, in the context of the present study, there is no significant difference between “conversion” and “recognition”. If a network reacts to a stimulus in a specific way, we can say that it recognizes the stimulus. If this reaction has a significantly different nature than the stimulus itself, we can say that the network converts the stimulus to some other representation form. In [10], the chaotic network had the properties of a converter/recognizer even in the absence of synaptic plasticity – just due to fluctuations in its structure. In our case, synaptic plasticity plays the key role – recognizing structures are formed as a result of self-organization process driven by synaptic plasticity.

Let us describe how we find A/P-recognizers in a network. The algorithm is based exclusively on analysis of neuron firing log and does not use information on connectivity. Since it is based on minimization of weighted error, first of all we give its definition. Let N_P be the number of different patterns in the input signal. Every pattern is presented n times. We record firing times of all excitatory neurons after every pattern presentation. We search for the presence of some structure E in these records (for example, it may be the event $e_2(i, j, a)$ meaning that the neuron j fires exactly a ms after the neuron i). Let us consider pattern A . Assume that structure E appears after n^+ presentations of A (true positives) and after n^- presentations of all the other patterns (false positives). Then the weighted error of recognition of the pattern A using the

structure E equals $\frac{n - n^+}{n} + \frac{n^-}{(N_P - 1)n}$.

The algorithm of finding A/P-recognizer for pattern A includes 3 stages.

1) *Creation of list \mathcal{S} of selective spike pairs.* For each pair of neurons (i, j) we find a delay a for which the event $e_2(i, j, a)$ gives the least weighted error. If the error is less than 0.5 and is less than the errors corresponding to a single spike of the neuron i or the neuron j , we put the triplet $\langle i, j, a \rangle$ to \mathcal{S} . Let us note that there exists a method to make this step time-efficient avoiding the iterations for all combinations of i, j and a . Upon completion of this step we sort \mathcal{S} in the order of increasing the weighted error.

2) *Creation of list \mathbf{G} of selective PNGs.* This step resembles the agglomerative clustering algorithm. PNG is defined as a set of pairs $\langle \text{neuron id, firing time} \rangle$. It is assumed that it always includes an element with firing time equal to 0. At the beginning of this step, \mathbf{G} is empty. In every iteration of the algorithm we take a successive triplet $\langle i, j, a \rangle$ from \mathcal{S} . If i and j do not enter any PNG in \mathbf{G} , we add $\{\langle i, 0 \rangle, \langle j, a \rangle\}$ to \mathbf{G} . If, for example, only j does not enter \mathbf{G} , while i enters $\mathbf{g} \in \mathbf{G}$ in the pair $\langle i, b \rangle$ we create a new PNG adding $\langle i, b + a \rangle$ to \mathbf{g} . If the weighted error of this new PNG is not greater than the error of \mathbf{g} we replace \mathbf{g} in \mathbf{G} by the new PNG. The weighted error of a PNG is calculated as weighted error of the event corresponding to the full activation of this PNG – when all its neurons fire at necessary times. If i and j belong to different PNGs from \mathbf{G} we merge these PNGs properly

shifting all firing times in one of them by the respective constant value. If the new larger PNG gives error not exceeding the errors of its parents, we remove these smaller PNGs from \mathbf{G} and insert the new PNG there. Having performed this operation with all elements of \mathcal{S} we get the final version of \mathbf{G} .

3) *Creation of A/P-recognizer.* As it was said, it can hardly be expected that a single PNG from \mathbf{G} would give a zero recognition error. Therefore, we are going to find the best ensemble of the PNGs from \mathbf{G} . We use a step-wise algorithm sequentially adding to the initially empty ensemble one PNG which gives the maximum error decrease until the moment when adding any new PNG leads to increased error. For ensemble P and support level N the error is defined as a weighted error of the event $e_P(P, N)$ – complete activation of at least N PNGs from P after pattern presentation. Then the error of ensemble P is the minimum of errors of $e_P(P, N)$ for all possible N .

The found ensemble is the sought A/P-recognizer. If the recognizer is exact (giving zero error for recognition of the pattern A) its quality can be evaluated using its *minimum selectivity* – the ratio of its minimum reaction to pattern A to its maximum reaction to any other pattern or its *mean selectivity* – ratio of its mean reactions to pattern A and to the other patterns. The reaction strength is measured as the total number of spikes emitted by all the active PNGs in the ensemble after pattern presentation.

A/P-recognizers are found with the help of this 3-step algorithm to neuron firing record related to the time when the network has reached its equilibrium state (or, as it is often called – after maturation period). The equilibrium state is determined by the absence of strong long-time trends of the main dynamic network parameters – like mean firing rate, total excitatory synaptic weight etc. Usually, synaptic plasticity mechanism forms the network equilibrium state for several thousand pattern presentations.

V. RESULTS

First of all, I would like to note that the results reported here should be considered preliminary. The main goal of this beginning stage of my research project was to demonstrate the fact that an initially chaotic SNN can generate as a result of an STDP-based self-organization process the structures playing the role of A/P-converter and unambiguously (with zero error) representing rate-coded input patterns. Needless to say, development of this research implies an evaluation of quantitative parameters of this phenomenon, its limits, requirements for SNN properties, maybe - a search for some of its neurophysiological correlates, etc.

The experiments aimed at empirical proof of the ideas of this work were performed with relatively small networks consisting of 1000 excitatory neurons (the number of inhibitory neurons varied). The input signal included 10 different patterns corresponding to partially intersected sets of input nodes. Expectedly, the problem of determining network parameters

TABLE I. THE MAIN PARAMETERS OF THE SNN REALIZING THE MOST SELECTIVE A/P-CONVERSION

Parameter	τ_R	τ	Number of inhibitory neurons	Number of synapses (EE/EI/IE/II)	LTD/LTP ratio (excitatory neurons)	LTD/LTP ratio (inhibitory neurons)
Value	3 ms	4 ms	116	7/43/12/18	0.8	7.68

TABLE II. THE CHARACTERISTICS OF CONVERSION QUALITY DEMONSTRATED BY THE BEST A/P-CONVERTER

Parameter	Minimum selectivity	Mean selectivity	Total number of neurons in all PNGs	Mean PNG size	Maximum PNG size
Minimum	2.83	161	17	3.5	5
Mediane	4.18	182	31	4.8	8
Maximum	8.5	224	40	5.7	12

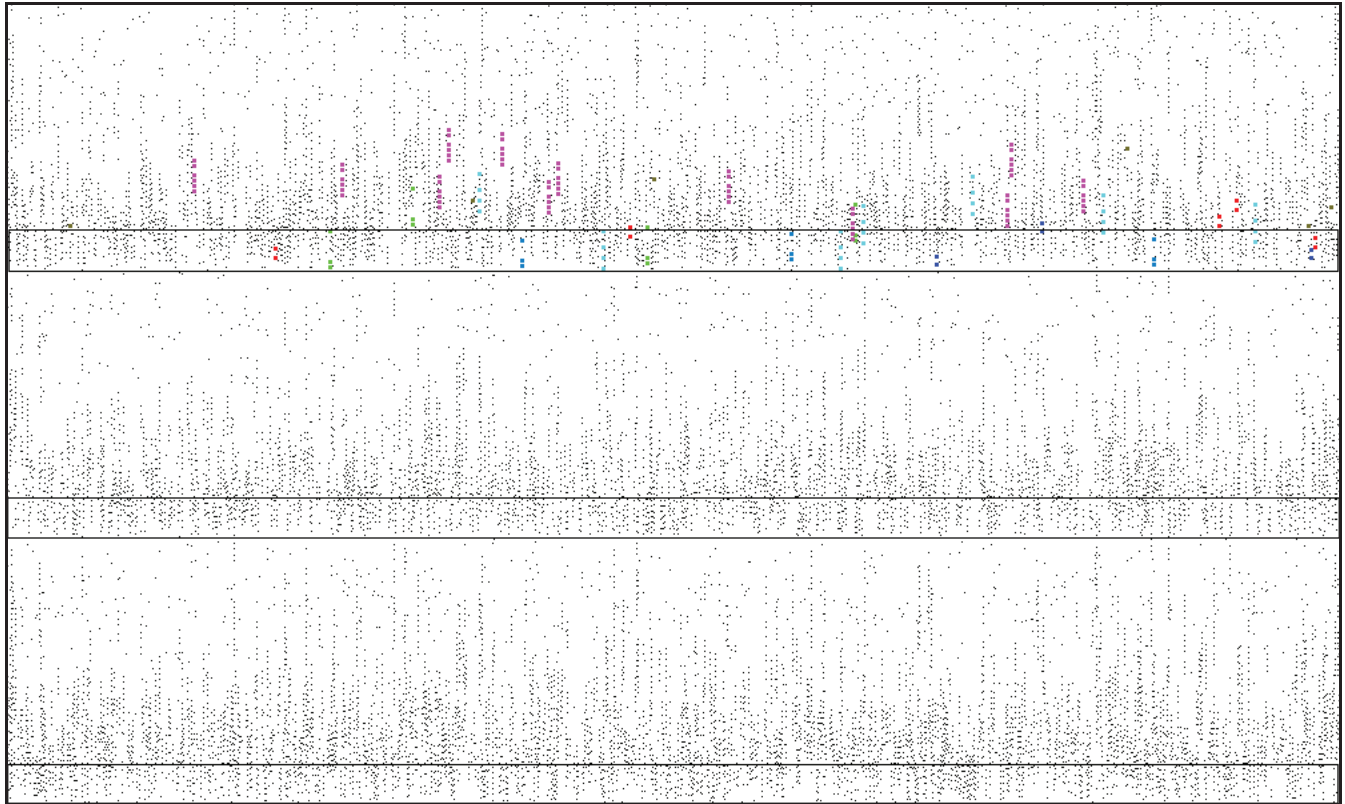


Fig. 1. Network reaction to various patterns. The horizontal axis corresponds to neuron number, the vertical axis is time. The narrow horizontal strips correspond to 30 ms episodes of pattern presentation. Period of pattern presentation is 200 ms. The fat colored dots are spikes emitted by PNGs entering A/P-recognizer for the uppermost pattern. Different colors correspond to different PNGs.

optimal from the point of view of A/P-recognizer accuracy was found to be theoretically intractable. It was only possible to estimate (very roughly) the network parameter boundaries confining the search space [13]. For this reason, numerical optimization on the basis of the genetic algorithm was used. The optimization criterion was the sum of lengths of lists \mathcal{S} for all the patterns (as a quickly evaluated parameter). The optimized parameters included number of inhibitory neurons, number of synapses of various kinds, various temporal characteristics (like τ and τ_R), STDP rule constants etc. – 36 parameters in total.

The main result obtained was successful creation of exact A/P-recognizers for all the patterns. The final population of networks in the genetic algorithm included several networks which contained in their equilibrium state exact A/P-recognizers. Interestingly, these best networks had quite different values of parameters – and therefore, we can suppose that the explored effect does not require careful parameter fine-tuning.

As an illustration, several most important parameters of the “winner” of the genetic algorithm are summarized in Table 1.

The characteristics describing the conversion quality for various patterns are presented in Table 2. An example of reaction of an A/P-recognizer to presentation of the recognized pattern and to 2 other patterns is depicted in Fig. 1.

Certain conclusions can be made even based on these first results. Firstly, we see that membrane time constant is quite small – so presynaptic spikes should come almost synchronously in order to make postsynaptic neuron fire. It seems natural – it is necessary for the exact timing of spike emission by PNG neurons. The network is very sparse – for example, every excitatory neuron is connected with only 7 presynaptic excitatory neurons. It is also explainable – sparse networks have more structure fluctuations necessary to form potentially selective PNGs. Interesting and unclear is the fact that relative efficiency of long-term synaptic depression (LTD) for inhibitory neurons is by order of magnitude greater than for excitatory neurons.

From Fig. 1 we can conclude that different PNGs become active with the different delays relative to pattern onset. The “blue” PNG reacts to pattern very promptly while the reaction of “pink” PNG begins after the end of pattern presentation but lasts a long time - up to 100 ms. By the way, it may mean that such PNG ensembles could realize the working memory mechanism like in [6]. But it should be noted that our model does not include short-term synaptic potentiation like [6] – this effect is explained exclusively by reverberating (and gradually fading) activity of specific neuronal ensembles.

VI. CONCLUSION

The reported research is devoted to a very interesting question – how neuronal ensembles can respond by strict spatio-temporal patterns of activity to rate-coded input signals. How does a structure of spike sequences precisely fixed in time appear from asynchronous streams of spikes? The present paper proposes a possible answer to this question. If we slightly re-formulate the problem, namely, if we admit some degree of asynchrony in the temporally coded response of the network to rate-coded stimuli then it becomes possible that the structures performing the desired conversion emerge in homogenous chaotic network in the process of its interaction with the external signal. Result of this beginning stage of our research is demonstration of the possibility to realize a synaptic

plasticity - based network self-organization process leading to the creation of a precise converter. The next steps should include a thorough experimental and theoretical study of this mechanism, analysis of its applicability to more realistic models of sensory signals and search for evidence of its possible role in information processing by various brain structures.

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