# Unsupervised Learning of Spatio-Temporal Patterns Using Spike Timing Dependent Plasticity

BanafshehRekabdar[1], Monica Nicolescu[1], Richard Kelley[1], MirceaNicolescu[1]

[1] Department of Computer Science and Engineering
University of Nevada, Reno
{rekabdarb, monica, rkelley, mircea}@cse.unr.edu

**Abstract.** This paper presents an unsupervised approach for learning of patterns with spatial and temporal information from a very small number of training samples. The method employs a spiking network with axonal conductance delays that learns the encoding of individual patterns as sets of polychronous neural groups, which emerge as a result of training. A similarity metric between sets, based on a modified version of the Jaccard index, is used for pattern classification. Two different neural connectivity models are evaluated on a data set consisting of hand-drawn digits that encode temporal information (i.e., from the starting to the end point of the digit). The results demonstrate that the approach can successfully generalize these patterns from a significantly small number of training samples.

**Keywords:** Spiking Neuron Network, Synaptic Plasticity, Polychronization, Unsupervised Learning, Classification, STDP

## 1 Introduction

This research is motivated by two robotic problems that rely on an autonomous system's ability to encode and recognize spatiotemporal patterns: intent recognition [1] and imitation learning [2][3]. In both domains, the activities observed by the autonomous system contain both spatial and temporal information. What is more important, however, is that both domains require that these patterns be encoded in a way that enables early recognition. We propose to address this problem through the use of spiking neural networks with axonal conductance delays, relying on a spike-timing dependent plasticity learning rule. Research by Izhikevich [4] has shown that spiking networks with axonal propagation delays can encode temporal patterns in the form of polychronous neuronal groups (PNGs). Several methods have been developed that exploit these mechanisms [5][6], but they employed a supervised learning mechanism for classification. Furthermore, they rely on large number of training samples. In this paper we propose an unsupervised method, which relies on small number of training samples. The remaining of the paper is structured as follows: Section 2 discusses relevant related research, Section 3 presents the details of our approach. Section 4 and 5 present the experimental results and conclusion respectively.

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## 2 Previous Work

Roboticists have explored a number of potential solutions to the intent recognition problem, including symbolic approaches [7] and probabilistic methods [1]. Biological neural networks offer an alternative to traditional statistical methods. Such networks pass messages through the timing of a spike train from one neuron to another. In biological systems, the connections between these neurons may be modified through experience; many researchers suspect that these modifications constitute the bulk of learning, and some researchers have attempted to use the biologically-inspired *spike-timing dependent plasticity* to do machine learning [8]. Although in general these systems have met with somewhat modest success, there are some indications that careful use of spike timings can facilitate very general forms of computation [9]. Moreover, researchers have shown preliminary work in which *polychronization* can be used with reservoir computing methods to perform supervised classification tasks [5]. Our work continues along these lines by exploring the extent to which purely unsupervised learning can exploit polychronization with temporally-dependent data to build time-aware representations that facilitate traditional classification. We differ from that previous work in our emphasis on mostly-unsupervised approaches, and in our emphasis on training from limited sample sizes.

## 3 General Approach

Our approach uses a network of spiking neurons with axonal conductance delays to perform classification of multiple spatiotemporal patterns. Our network consists of 320 neurons. Each neuron is connected to 0.1% of the rest of the neurons(32 synapses).Each synapse has a fixed conduction delay between 1 ms to 20 ms. The delays are randomly selected using a uniform distribution. Each neuron can be either excitatory or inhibitory and the ratio of excitatory to inhibitory neurons is 4:1.Synaptic weights are initialized with +6 if the corresponding neuron is excitatory and -5 if the neuron is inhibitory. The maximum value for the weights is 10.We use two different probability distribution functions to establish the connectivity between neurons: a uniform distribution and a two-dimensional Gaussian distribution with a standard deviation equal to 3.

Our domain dataset consists of handwritten digits from digit *zero* to digit *nine*, stored as a grey-level image with width and height of 16 pixels. In addition to the spatial information inherent in the patterns, we also encoded temporal information regarding how the pattern was drawn: from the first pixel (beginning of pattern) to the last (end of pattern) the intensity of the pixels decreases from highest to lowest (fade tapering). Thus, we can use an intensity-based image to encode a relative temporal relation. From the pixel intensity values we then generate a time-firing pattern that consists of a list of the neurons in decreasingly sorted order from highest to lowest intensity values.

During training, each pattern is presented to the network during 1-second intervals as follows: the neuron that corresponds to the highest intensity value will be stimulated first (by providing it with input current of 20 mA), followed by the lower intensity value neurons in decreasing sorted order.

Polychronization in spiking neural networks is a property to exhibit reproducible time-locked but not synchronous firing patterns with millisecond precision [5][9]. Using the trained network we build a model of each class, consisting of all the persistent PNGs that are activated by a pattern from that class. In this work, we consider PNGs that have 3 anchor neurons. To find all the PNGs corresponding to a pattern, we take all possible combinations of 3 neurons from the corresponding timed pattern and we stimulate these subsets of neurons in the network in the same order and using the same timing as in the pattern. If a PNG with a path length of at least 3 is activated, then it is added to the set corresponding to the pattern's class. For each class, the result will be a group of PNG sets. Each PNG is uniquely identified by its anchor neurons. In the testing phase, for a particular testing pattern, we stimulate all possible combinations of 3 anchor neurons using the correct order and wait for 500ms, and consider the PNGs that have a minimum path length of 3. Next, we find the similarity between the PNG set of the testing sample and all training models. We choose the class of the sample from the training set that results in the greatest similarity measure. We adapted a similarity measure for sets called Jaccard Index [10]. If A and B are two PNG sets corresponding to two patterns, the similarity measure between A and B is:

$$sim(A,B) = 1 - \frac{|A xor B\,|}{|A \cup B|} \tag{1}$$

## 4 Experimental Results

We created a dataset of handwritten digits (5 training and 22 testing samples for each digit.) We computed the following measures: i) the *success rate* (the percentage of correctly classified test samples), ii) the *error rate* (the percentage of misclassified test samples), and iii) the *rejection rate* (the percentage of instances for which no classification can be made). Rejected patterns occur when the similarity measures are all zero or we have a tie between multiple classes. Tables 1 and 2 show our results.

**Table 1.**Multi-classclassificationresultsfor a network with Gaussian distribution

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | All digits |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Success rate | 77.2% | 77.2% | 81.8% | 68.1% | 90.9% | 86.3% | 86.3% | 95.4% | 45.4% | 90.9% | 80% |
| Error rate | 13.6% | 13.6% | 9% | 27.2% | 4.5% | 9% | 13.6% | 4.5% | 50% | 9% | 15.4% |
| Rejection rate | 9% | 9% | 9% | 4.5% | 4.5% | 4.5% | 0% | 0% | 4.5% | 0% | 2.5% |

**Table 2.** Binary classificationresultsforclasses: i) 0 versus 1 andii) 5 versus 8

| | Gaussian0 vs. 1 | Random0 vs. 1 | Gaussian5 vs. 8 | Random5 vs. 8 |
|---|---|---|---|---|
| Success rate | 83.3% | 32% | 84.7% | 56% |
| Error rate | 0% | 0% | 0% | 0% |
| Rejection rate | 16.6% | 67% | 15% | 43% |

## 5 Conclusion

In this paper we have introduced a new unsupervised approach for learning spatiotemporal patterns. Our method utilizes a network of spiking neurons to learn from a very small training set. The general idea behind our approach is that a spiking network with axonal conductance delays, learns the encoding of each spatiotemporal pattern as a set of PNGs. In our experiments we have tested two different neural connectivity approaches, one with a uniform probability distribution function and second with a Gaussian probability distribution. Our results show that the Gaussian connectivity model performs better and despite the very small number of training samples, our approach has successfully generalized to new and different unseen patterns.

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