Self-Organized Spiking Neural Network Model for Data Clustering

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1 Introduction

In recent modern era of neural networks technology, a model called Spiking Neural Network (SNN) was born. This SNN was classified by Maass [1] as the third generation of neural networks. It is a new kind of neural network which is inspired and motivated by the biological neurons ways of communication. The biological neurons communicate with each other through the media of action potentials, often called pulses or spikes. This is a well-known aspect of real neurons, which transmit information by voltage pulses of the membrane potential.

SNN has been much considered in attempt to achieve a more biologically inspired artificial neural network. The objective of the SNN as the name implies, tries to overcome the over simplification of the ANN system and emulate the pulse system to come out with a more biologically realistic neural system.

This paper presents a preliminary investigation and development of the unsupervised learning processes in SNN. This learning mechanism is extended to one of the most successful paradigm of unsupervised learning: the Kohonen Self-Organizing Maps [3]. Hence, a Self-Organized SNN based on Spike Respond Model (SRM) is constructed. Spiking neurons with delays to encode the information is suggested. Thus, each output node will produce a different timing which enables competitive learning. The model is designed and programmed in MATLAB environment. Further simulation analysis was performed to observe the network self-organizing learning and its topology preservation behavior. The model is further assessed with real-world dataset for data clustering simulation.

2 Self-Organized SNN Architecture

There exist various kinds of spiking neuron models. The neuron model presented here is based on the simplified model of the Spike Response Model introduced by Gerstner [2]. This model is further structured to form a self-organized SNN architecture. The network architecture is illustrated in Fig. 1. The diagram illustrates the basic architecture of self-organized SNN. The presynaptic neurons (the inputs) are each of them connected to all the postsynaptic neurons (the output layer). In this diagram the inputs are n dimensional elements and the output has 5x5 layer structure. Every time a set of n dimensional element input is presented to the network, a spike potential with different delays travel across each connection. These neurons will compete with each other and through some distance measurement the winner is chosen. Through this process, the neurons are expected to organize themselves in the topology preserving grid.

The Self-Organized SNN architecture can be categorized into three main processes i.e. initialization, delay adjustment and self-organization.

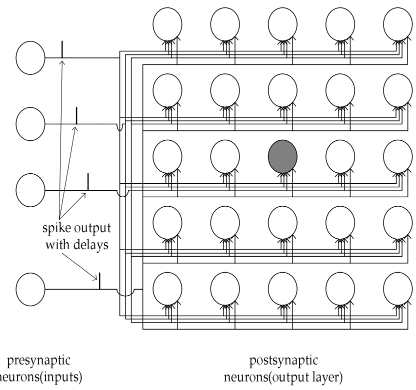

Fig.1. A basic architecture of 5x5 self-organized SNN

2.1 Initialization

In this stage, the presynaptic neurons (as illustrated in Fig.1) are pre-process before the learning phase. Initial random values of inputs are set and transform into temporal inputs. Assumption is made that each neuron is firing only once i.e. one spike per neuron, each neuron of the input layers hold the value of each inputs; dependent on the dimension of the inputs.

2.2 Delay adjustment

The connection strength of the input-output strength can be determined by delays. The delay is given by the difference between the presynaptic neuron firing time and the time the postsynaptic potential starts rising.

2.3 Self-Organization

The Self-Organized SNN organizes its neurons into an input network layer and an output network layer. Each neuron in the input layer is connected to each neuron in the output layer. The two-dimensional output layers act as a map where each neuron is positioned. For this winning measurement we use the shortest Euclidean distance $\|\textit{temporal inputs} - \textit{delays}\|$ between the input and the competing neurons.

3 Simulation Results

3.1 The Self-Organized SNN

Fig. 2 displays a simulation result of the above mentioned algorithm in section 2. In this case the inputs are two-dimensional which is sequentially feed and applied to the network. Each input is assigned with an arbitrarily small value of delay. The output activation is calculated at each run by measuring the difference of the inputs and the delays value.

Through this process, the node that fired the quickest spike is chosen as the winner.

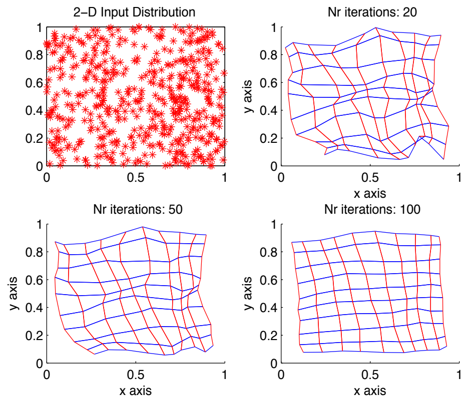

Fig. 2. Self-Organized SNN Simulation Result

3.2 Data Clustering

The proposed Self-Organized SNN was further assessed with real-world dataset for data clustering. The objective was to analyze the effectiveness of the architecture on data analysis exploration. The Glass Identification dataset from UCI Repository [7] was used for the experiment.

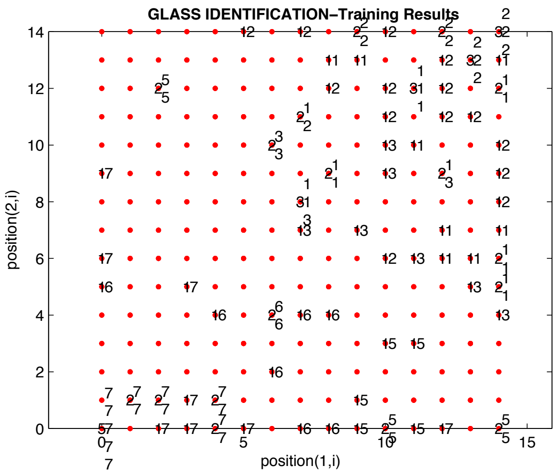

Fig. 3. Example of Glass data Training results with 1000 epochs

4 Conclusion

The experimental results showed that Spiking Neural Networks is able to be implemented in self-organized learning. Few publications have been reported relating to the implementation of Spiking Neural Network in self-organization networks [4, 5 and 6]. However, the research on Self-Organizing Spiking Neural Network is still an open discussion. Researchers reported different models with different approaches.

The Self-Organized SNN which was presented in this paper, contribute another perspective of the Spiking Neural Networks unsupervised learning. The learning computes the delay of the input-output neurons for its competitive process. This method is an advantage because a straightforward Euclidian distance measurement can be used.

The experimental results had also shown the application of self-organized SNN on data clustering. The network was trained and tested on Glass data sets. The training and testing simulation results show that the network is capable to perform to some extent the desired results.

Acknowledgements

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