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A Hybrid Spiking Neural Network Model for Multivariate Data Classification and Visualization

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Abstract— **This study proposes a hybrid model of Self-Organizing Map with modified adaptive coordinates (SOM-AC) and Spiking Neural Network (SNN) for multivariate spatial and temporal data visualization and classification. SOM is one of the most prominent unsupervised learning algorithms. Recently, many extensions for SOM have been proposed for temporal processing. However, none of the extensions uses spikes as means of information processing. SNN has potential for qualitative advancements in both biological relevancy and computational power. Therefore, this hybrid learning model is proposed to harness the advantages of both SOM-AC and SNN to produce intuitive multivariate data classification and visualization. Empirical studies of the hybrid model using synthetic and benchmarking datasets yielded promising classification accuracy and intuitive rich visualization.**

Keywords- Spiking Neural Networks; self-organizing; coincident detector; modified adaptive coordinate; unsupervised learning; intuitive visualization

I. INTRODUCTION

Every real event happens in time and space. Although the importance of time or space information might vary according to different event, without either one, the descriptions of the event become incomplete. The ability to process not only the spatial information but also the temporal component is behind recent explosive growth of researches in the third generation of Artificial Neural Network (ANN) [13] which is also known as Spiking Neural Networks (SNN).

With accumulating biological and experimental discoveries [4, 5, 6], the learning paradigm of neural information processing is shifted. Instead of just firing rate, the exact timing of spike is found to be conveying most of the information [8, 16, 20]. SNN is now generally being accepted as biological more plausible and computationally more powerful than sigmoidal based Artificial Neural Network (ANN) [12, 13, 14]. However, one major problem arises while trying to implement SNN in solving practical problems. Not all applications are temporal based. Solving spatial problems in temporal domain introduces unnecessary complications. Therefore, this study proposes a hybrid learning model based on Self Organizing Map with modified Adaptive Coordinates (SOM-AC) [19] and SNN.

SOM is the most popular unsupervised ANN learning algorithm in the market. It has been successfully implemented in signal processing, control engineering, medical diagnosis, financial analysis and many other complex applications. However, the original SOM's winner-take-all competitive learning algorithm often performs poorly in differentiating sequential or temporal patterns. Many variations of the original SOM algorithm were proposed to improve its performance in processing sequential or temporal data [21, 22, 23, 24]. The variations took account of the effect of previous samples on existing sample of a sequential data. Nonetheless, the variations did not use spikes as means of information transmission and processing. On the other hand, SNN being temporal based architecture is more natural in processing sequential data.

Intuitive visual information is often very useful for human based diagnosis and intervention. However, original SOM based ANN or SNN architecture is unable to provide the system user with such information. Therefore, modified adaptive coordinate [19] is hybridized into the learning algorithm to produce an intuitive, topologically preserved visualization. This proposed hybrid model can accommodate for both spatial and temporal data with simple transformation from one form to the other.

An important assumption of this proposed model was in the storing of temporal information as spatial values. As proposed in [19], temporal data is encoded in spatial domain as weights. Since weights are discrete values, weights adaptation according to the SOM's unsupervised competitive learning algorithm model is excellent for the task.

SNN is capable of achieving promising qualitative advancement as compared to the second generation ANN. Figure 1 illustrates this idea. It shows the membrane potential of a single spiking neuron in response to XOR inputs. Inputs "0 0" and "1 1" produced similar membrane potential pattern while inputs "0 1" and "1 0" produced another pattern of membrane potential. Calculating output spike timing of the spiking neuron in response to the inputs, non-linearly separable XOR inputs can now be classified linearly. This decoding method was consistent with the finding that significant neurons information was transferred in the first spike [20].

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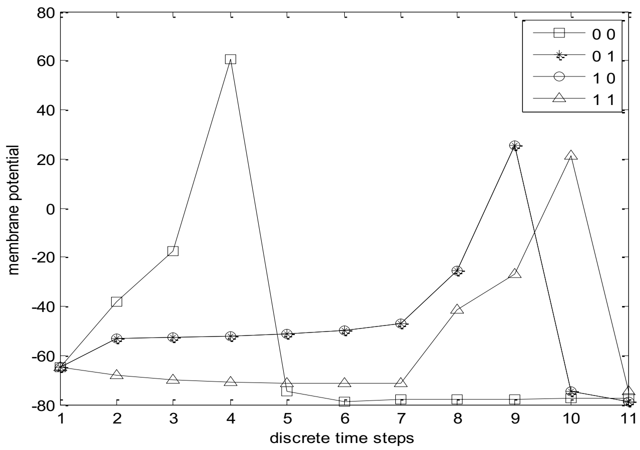


Figure 1. Membrane potential for a spiking neuron in respond to XOR inputs. Threshold = 20, Spike potential = 15, Input window = 11.

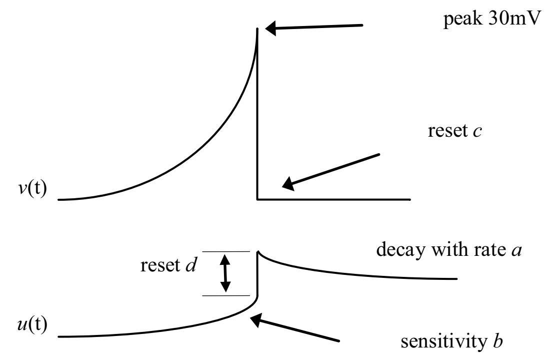


Figure 2. Effect of parameters a, b, c, and d on membrane potential response (adapted from [9]).

Section II briefly introduces the SNN model; the information processing and encoding technique used in this study. Section III proposes the self-organizing map with modified adaptive coordinates learning model of SNN in multivariate data classification and visualization. Section IV demonstrates the applicability of the proposed model in classifying and visualizing synthetic Gaussians datasets and also a real life control chart problem. Section V concludes the study.

II. SPIKING NEURAL NETWORK – INFORMATION PROCESSING AND ENCODING TECHNIQUE

It is not the goal of this study to show the biological plausibility of the proposed model. Instead, this study examines the applicability of the proposed SNN model in solving practical problems. Nevertheless, the selected processing and encoding technique are biologically plausible.

Spiking neuron model according to [9] is selected as the processing unit. The choices of a, b, c, and d parameters enable this model to produce various known cortical firing patterns [10]. This model consists of;

$$v' = 0.04v^2 + 5v + 140 - u + I \quad , \qquad (1)$$

$$u' = a(bv - u) \quad , \qquad (2)$$

and the auxiliary after-spike resetting

$$if\, v \ge +30mV, \;\; then \begin{cases} v \leftarrow c \\ u \leftarrow u + d. \end{cases} \qquad (3)$$

The v and u here are dimensionless variables representing membrane potential and membrane recovery potential and a, b, c, and d are dimensionless parameters. I is the synaptic current or the input spike and $' = d/dt$. The effect of setting different parameters values on the membrane potential variables v and u can be seen in Figure 2.

The spiking neuron will generate an action potential or spike whenever the membrane potential exceeds the peak voltage +30mV from below. This peak voltage normally is referred as the firing threshold value. This time-dependent feature of spiking neuron makes it very unique in signal processing. Multiple input spikes will not cause the neuron to generate action potential if there are significant delays between input spikes. Ideally, only input spikes with similar arrival time will generate post-synaptic spike.

Deriving from this time dependent property of spiking neurons, numerous learning algorithms were proposed to tune or adapt the synapses' efficacies or the weights of the spiking neurons. Tuned efficacies will generate similar timing of post-synaptic spikes for a particular class or cluster of inputs; that is the spiking neurons act as coincident detectors. Differing from ANN that normally uses activation rate for information processing, SNN uses exact post-synaptic spikes' timing of a particular spiking neuron to differentiate between input classes. Figure 3 illustrates this concept.

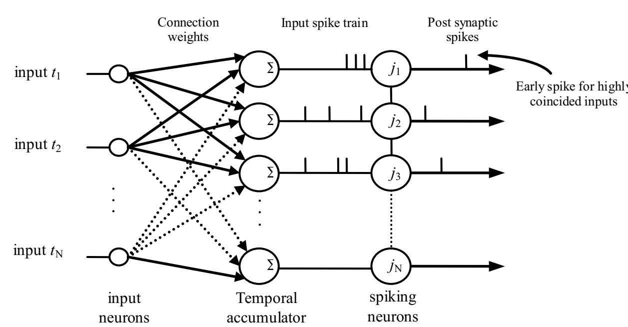


Figure 3. Proposed network architecture

An encoding component is required in order for the model to process spatial data. 1D encoding proposed in [1] is used in this study. It's a linear transformation of single spatial value into single discrete temporal value using;

$$y(f) = \frac{(b-a)}{range} \times f + \frac{(a \times Max - b \times Min)}{range} \quad , \qquad (4)$$

where f represents the spatial value, [a, b] represents the intended temporal interval, (Max, Min) represents the maximum and minimum values in the spatial space, and $range=Max–Min$. 1D encoding maintained the input data dimensions making it more computationally cost efficient as compare to sparse encoding proposed in [3].

III. Proposed Network Architecture and Hybrid Learning Algorithm

Each temporal signal consists of temporal and non-temporal components. For a discretized D-dimensional temporal random variable training dataset V of M samples, V= $\{v(n)_m^d\}$ ($m=1,\ldots,M$, $d=1,\ldots,D$, and $n=Z^+$), let L be the SOM lattice of N neurons with weights vector, $\boldsymbol{w}_i(t)\in v$ ($i=1,\ldots,N$) at training iteration t. To make sure each sample generates at least one post synaptic spike, the activation window is set to a large number until a spike is generated as the result of an input sample. To increase the differentiation ability among the neurons, the pre-synaptic spikes' potential are initialized according to;

$$T/S.D \tag{5}$$

where T is the minimum threshold value that will trigger a post-synaptic spike within the activation window, D is the dimension of the dataset and S is the sensitivity parameter in range 0~1. This is assuming pre-synaptic spikes must coincide according to S percent in order to generate a post-synaptic spike; that is the highest sensitivity of the SNN to discriminate between the input samples.

SOM learning algorithm [11] involves finding winner neuron for each sample **x** drawn from dataset, using Euclidean norm

$$i^* = \underset{i}{\operatorname{argmin}} \left\| x\text{-}w_j \right\| \quad , \tag{5}$$

After winner neuron is found, the weights of the SNN is updated using SOM learning algorithm;

$$w_j(t+1) = w_j(t) + \eta . h_{i^*j}(t)\left[x(t) - w_j(t)\right] \quad , \tag{6}$$

where η is the learning rate and $h_{i^*j}(t)$ is the Gaussian neighborhood function

$$h_{i^*j}(t) = \exp\left[-\frac{(r_{i^*} - r_j)^2}{2\sigma(t)^2}\right] , \tag{7}$$

$(r_{i^*} - r_j)$ is the spatial distance between winner neuron i^* and neighborhood neuron j and

$$\sigma_\wedge(t) = \sigma_{\wedge 0} \exp\left(-2\sigma_{\wedge 0}\frac{t}{t_{\max}}\right) \tag{8}$$

is the neighborhood range with initial value $\sigma_{\wedge 0}$.

Although SOM is highly robust in producing topology preserved weights resembling the data structure, SOM's rectangular or hexagonal grid does not preserve the output map. This makes its final visualization lacks intuitive information about the clustering tendency of the data being analyzed. In order to project this clustering tendency in a more natural way, that is topology preserved output map, modified Adaptive Coordinates (AC) [20] is hybridized into the learning algorithm. Modified AC introduces extra set of adaptive units$\langle ax_i, ay_i \rangle$ that mirror the Euclidean distances between neurons' weights. Instead of using rigid grid as in SOM lattice, these AC units can move freely on a 2D lattice mirroring the changes in the neurons' weights. The AC units are updated according to (9).

$$\begin{aligned} ax_i(t+1) &= ax_i(t) + \Delta Dist_i(t+1)\sigma_\wedge(t)\left(ax_c(t) - ax_i(t)\right) , \\ ay_i(t+1) &= ay_i(t) + \Delta Dist_i(t+1)\sigma_\wedge(t)\left(ay_c(t) - ay_i(t)\right) , \end{aligned} \tag{9}$$

where the adaptation factor

$$\Delta Dist_i(t+1) = d_{out}(t) - d_{in}(t) \quad , \tag{10}$$

is the difference of Euclidean distance between adaptive units and their respective neurons' weights. $\sigma_\wedge(t)$ is the neighborhood range according to (8). The details of the algorithm can be found in [20].

Proposed hybrid SOM-AC and SNN algorithm is;

i. Transform spatial data to temporal form according to (4).
ii. Randomly initialize neurons' weights $\boldsymbol{w}_i$.
iii. Draw a training sample from the dataset.
iv. Construct pre-synaptic spike train.
v. For each training sample, find the winner neuron according to (5) and also neuron that spike first.
vi. Update the connection weights according to (6).
vii. Adapt the AC units according to (9).
viii. Repeat step ii to vii for pre-specified number of iterations.

In order to reduce computational cost, AC units adaptation only starts after SOM almost converge, that is after 1/6th of the total numbers of iteration.

IV. Experiments

Experiments were conducted to demonstrate the visualization and classification ability of the proposed model in mining not only the multivariate spatial data, but also the temporal data. The first set of experiments were conducted using spatial datasets. The datasets consist of three synthetic Gaussians datasets and two benchmarking datasets. These experiments show the hybrid model able to perform multidimensional reduction and produced topological preserved visualizations.

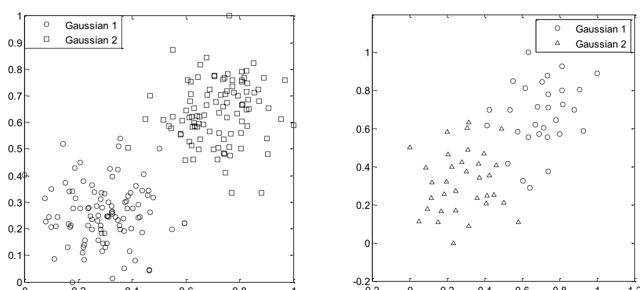
Second experiment was conducted using generated control chart dataset [17]. The second experiment demonstrated that the proposed hybrid model was not only capable of producing dimensional reduction and good visualization, it was also able to mine discretized sequential data with higher classification accuracy than the original SOM.

In all these experiments, spiking neurons' parameters were set according to the suggestion made in [9]; a=0.02, b=0.2, c=-65, and d=2. The threshold value was set to 30mV, learning rate, η was set to be linearly decreasing from 0.35 to 0.01 and initial sigma, $\sigma_{\wedge 0}$ was equal to half of the SOM lattice. For ease of visualization, the lattice was set to be a square and final results were normalized. The 8x8 SOM map together with 8x8 AC units were used.

A. Simulated Gaussians and Benchmarking Datasets

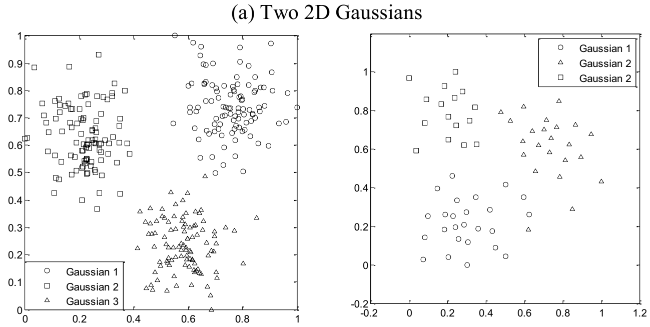
Three simulated Gaussians datasets were used to demonstrate the effectiveness of the proposed hybrid model in producing topological preserved visualizations. The 3D Gaussians dataset was generated according to [25]. Figure 4 (a) and (b) show the visualizations resembled closely to the data distribution. The clusters and density information of the data were clearly visible in the 8x8 SOM-AC visualizations. Figure 4 (c) shows the visualization after the dimensional reduction from 3D to 2D was performed. The visualization was able to preserve the clusters and density information even after the dimensional reduction.

To further demonstrate the usefulness of the proposed hybrid model for real world applications, two benchmarking datasets from online UCI Machine Learning Repository [26] were used. First benchmarking dataset used was the Iris flowers dataset. It consisted of 3 classes of data with 50 samples each. Each sample was made up of four parameters or 4D data. The second dataset Ionosphere consisted of 2 classes of data with total of 351 samples. Each sample was made up of 34 parameters or 34D. Interesting patterns were revealed in these visualizations.



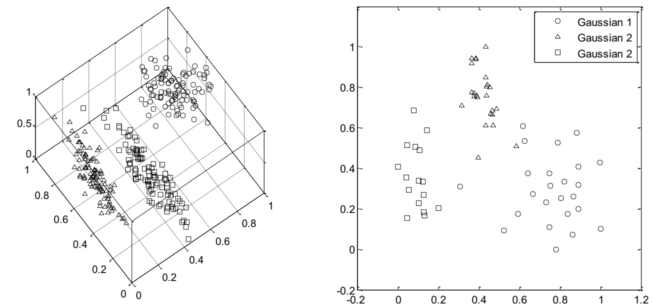
Data plot | 8x8 SOM-AC Visualization

(a) Two 2D Gaussians



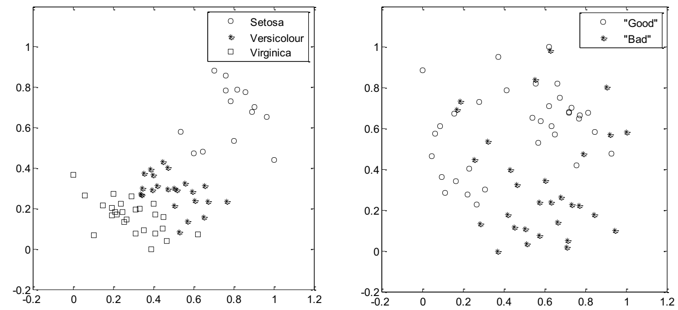
Data plot | 8x8 SOM-AC Visualization

(b) Three 2D Gaussians



Data Plot | 8x8 SOM-AC Visualization

(c) Three 3D Gaussians



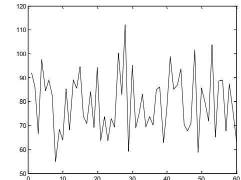
(d) 8x8 SOM-AC Visualization of Iris dataset – 4D | (e) 8x8 SOM-AC Visualization of Ionosphere dataset – 34D

Figure 4. 2D visualizations on synthetic and benchmarking datasets

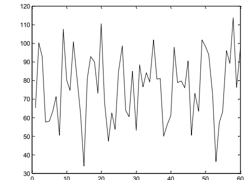
B. Control Chart Dataset

Control chart dataset was generated using formulae given in [16]. It consisted of six patterns as shown in Figure 5. There were 250 samples generated from each pattern producing a dataset of 1500 samples. Each sample consisted of 60 discrete data points. Two third of the dataset was used during training phase and the remaining samples were used to test the classification accuracy. Table 1 shows the average classification accuracy of ten trials. SNN was able to produce higher classification accuracy as compared to classical SOM.

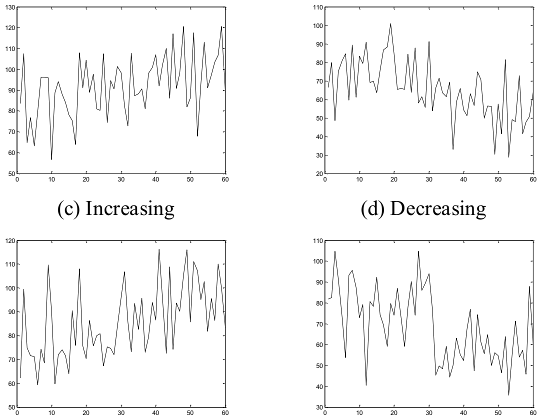
Figure 6 shows the SOM-AC 2D visualization of the Control Chart dataset. Taking the 60 discrete data points of each data sample as the dimension of the data, this visualization actually performed a dimensional reduction from 60D to 2D. Yet, six clusters of AC units that represented the six patterns of the control chart dataset were clearly revealed in the projection. The Normal pattern, the AC units labeled with circles, lied at the center of the projection while the other patterns were traced away from the center. Patterns that were similar such as increasing and upshift clustered together closely. This visualization was consistent with intuitive perception.



(a) Normal



(b) Cyclic



(c) Increasing (d) Decreasing

(e) Up shift (f) Down shift

Figure 5. Six control chart patterns

TABLE I. CLASSIFICATION PERFORMANCE COMPARISON

Dataset	**SNN**	**SOM**
Control Chart	97.56	96.93

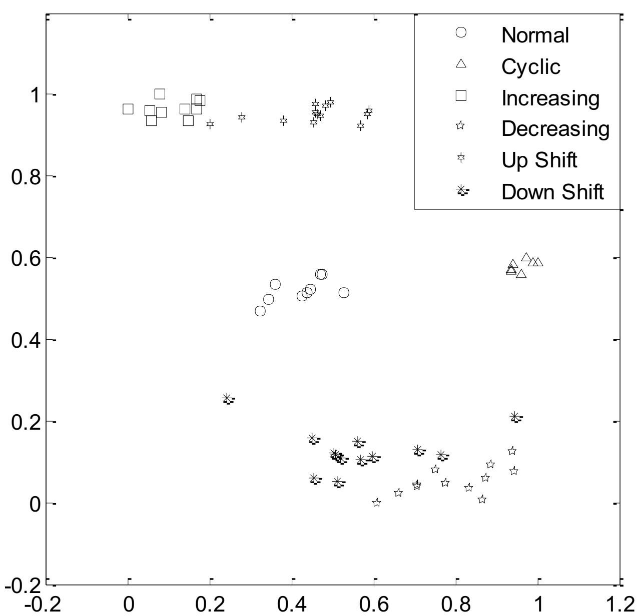


Figure 6. 8x8 SOM-AC 2D visualizations for control chart dataset

V. CONCLUSION

SNN is the latest trend of development in neural network community inspired by the neuroscience discoveries. SNN being temporal based architecture makes it more natural in mining real life data.

The proposed hybrid SOM-AC and SNN model are able to produce rich visual information for intuitive decision making. This hybrid model shows promising performance not only for spatial data, but also the temporal data. Spatial to temporal transformation enhancement, alternative decoding schemes and projection of spike information unto the visualization are three areas of ongoing research.

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