OCTASOM- AN OCTAGONAL BASED SOM LATTICE STRUCTURE FOR BIOMEDICAL PROBLEMS

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ABSTRACT. In this study, an octagonal-based self-organizing network's lattice structure is proposed to allow more exploration and exploitation in updating the weights for better mapping and classification performances. The neighborhood of the octagonal-based lattice structure provides more nodes for the weights updating than standard hexagonal-based lattice structure. Based on our experiment, the octagonal-based lattice structure performance is better than standard hexagonal lattice structure on biomedical datasets for classification problem. This indicates that proposed algorithm is an alternative lattice structure for self-organizing network which give more wisdom to classification problems especially in the biomedical domains.

Keywords: self-organizing network, octagonal-based lattice structure, classification problems, biomedical datasets

INTRODUCTION

SOM has been known as clustering, classification and optimization algorithm in artificial neural network (ANN). Other types of ANN's architecture such as backpropagation (BP), is good for classification problems but slow in convergence time (Shamsuddin, Darus, & Suliman, 2002; Shamsuddin, Hassan, & Hua, 2012; Hassan, Quo, & Shamsuddin, 2012). While, Kohonen self- organizing map (SOM) algorithm provides high to low dimensional mapping architecture which involves competitive, cooperative and adaptive scheme. However, standard SOM suffers from a number of serious limitations that hinders its performance, particularly in pattern clustering or pattern classification (Weijian & Fraser, 1999). Furthermore, the performance of SOM depends heavily on optimal combination and initialization of weight initialization, input sequence, best matching unit (BMU), distance function, neighborhood function, adaptation rule, learning rate, network size, network architecture, accuracy test, learning mode, convergence and termination criteria. Consequently, those parameters can improve the quality of network mapping, training time, convergence time and accuracy (Nour & Madey, 1996). The quality of Kohonen map is also determined by its lattice structure since the weights of each neuron in the neighborhood will be updated beyond the lattice area. Therefore, we proposed an octagonal-based SOM lattice structure which so-called OctaSOM for better mapping and classification performances.

The remainder of this paper is organized as follows: next section describes the related work on SOM algorithm; followed by the explanation on the proposed method, experimental result and analysis. Finally, conclusion of the study.

RELATED WORK

Self Organizing Map (SOM) was first introduced by von der Malsburg (1973) and presented by Professor Teuvo Kohonen in 1982. The goal of SOM network is to map high dimensional input signal into a simpler low dimensional discrete map. SOM are based on competitive learning, where the output nodes compete among themselves to be the winning node and the only node to be activated by a particular input observation (Hayin, 1999). Conventionally, SOM learning algorithm is synonym with the clustering concept due to the adaptation process which produces a group of output patterns. The process of SOM training can be categorized either unsupervised or supervised. Supervised SOM contains actual input signal and a vector which predetermines the output class; pre-determine class of each input signal in the training set. These corresponding class values must be used during training. During recognition of new sample, only its single part is compared with the corresponding part of the weight vectors. On the other hand, the unsupervised SOM learns by making up a map topology and preserving representation of the statistical distribution of all input data. SOM's algorithm exhibits three characteristic processes which is competition, cooperation and adaptation.

Many studies have been done on comparing the lattice structure of SOM, for instance, comparative study on standard SOM and Spherical SOM (Brennan & VanHulle, 2007; Hung, 2008; Matsuda & Tokutaka, 2011), an Emergent SOM (Poelmans, Elzinga, Viaene, Dedene, & Hulle, 2009) while enhanced hexagonal SOM (Bariah, 2007;Hassan & Shamsuddin, 2011). Hexagonal lattice structure is good for image processing since the structure can make the image pixel uniform to each other. While does not favor to horizontal or vertical directions (Middleton, Sivaswamy & Coghill, 2001; Kohonen, 2001). Spherical and Torus SOM structures are focus on topological grid mapping structures rather than improvement on lattice structure. The aim of these topological structures is to eliminate the border effect issues and generally apply in clustering and visualization area (Marzouki & Yamakawa, 2005; Nakatsuka & Oyabu, 2003; Matsuda, Tokutaka, & Oyabu, 2009). The plane lattice gives a better view of the input data as well as a closer links to edge nodes that makes the 2D visualization of multivariate data possible using SOM's code vectors (Kihato, Tokutaka, Ohkita, Fujimura, Kotani, Kurozawa & Yoshio, 2008).

From previous studies, it is well known that using a neighborhood function with a large width is effective in creating an ordered map from a very random initial condition (Aoki & Aoyagi, 2007). A narrow neighborhood function can cause topological defect; kink state and network map twisted for one dimensional and two dimensional maps respectively. Therefore, in many cases, the width of the neighborhood function is initially set to be large, such as half the width of the array of units, and is gradually decreased to a small final value. Hence, in this paper, we proposed an octagonal-based lattice structure, so-called OctaSOM as an alternative presentation for SOM lattice structure. The detail explanation is given in next section.

OCTAGONAL-BASED SELF ORGANIZING MAP (OCTASOM)

In this study, an octagonal-based lattice area formulation is presented in equation (1). Unlike conventional hexagonal lattice as in equation (2), a neighborhood of the proposed formulation is given, where the neighborhood function, $\Theta_{Oct}(t)$ is used instead of the neighborhood width, $\Theta_{Hex}(t)$. Since $D(t)$ is a threshold value, it will decrease gradually as training progresses. For this neighborhood function, the distance is determined by considering the distance of each dimension. The dimension with the maximum value is chosen as distance node from BMU, $d(j)$. $\sigma_{Oct}(t)$ and $\sigma_{Hex}(t)$ corresponds to the width of an octagonal and hexagonal-based lattice, respectively.

$$\sigma_{Oct}(t) = 8 \times \sigma(t)^2 \times (\sqrt{2} - 1) \quad , \tag{1}$$

$$\sigma_{Hex}(t) = 6 \times \frac{1}{2} \times \sigma(t) \times \sqrt{(\sigma(t)^2) - (\frac{1}{4}\sigma(t)^2)} \quad , \tag{2}$$

where $\sigma_{Oct}(t)$ is standard octagonal lattice, $\sigma_{Hex}(t)$ is standard hexagonal lattice, $\sigma(t)$ is neighborhood radius.

$$\Theta_{Oct}(t)\begin{cases} 1 & d(j) \le D(t) \\ 0 & d(j) > D(t) \end{cases} \quad . \tag{3}$$

The weights of all neuron within this improve octagonal area are updated with $\Theta_{Oct}(t) = 1$, while the others remaining unchanged. As the training progresses, this neighborhood gets smaller, resulting to the neurons that are very close to the winner, and will get updated towards the end of the training. For neighborhood width, radius is reduce with exponential decay function,

$$\sigma(t) = \sigma_0 \exp\left(-\frac{1}{\lambda}\right), t = 1,2,3,... \tag{4}$$

where σ_0 is initial radius, λ is maximum iteration and t is current iteration.

The neighborhood function, $\Theta_{Oct}(t)$ is defined as,

$$\Theta_{Oct}(t) = \exp\frac{-d(j)^2}{\sigma_{Oct}(t)} \tag{5}$$

For updating OctaSOM:

$$x(t+1) = x(t) + \Theta_{Oct}(t) \times L(t) \times (V(t) - x(t)) \tag{6}$$

$$L(t) = L_0 \exp\left(-\frac{t}{\lambda}\right), t = 1,2,3,... \tag{7}$$

where $L(t)$ is learning rate, $V(t)$ is input vector and $x(t)$ is weight vector at iteration t.

Furthermore, the proposed method will be trained and tested with six biomedical datasets (appendicitis, heart, hepatitis, Pima Indian diabetes, Wisconsin breast cancer and mammographic dataset) from KEEL dataset repository (Alcalá-Fdez, Fernandez, Luengo, Derrac, García, Sánchez, & Herrera, 2011). Meanwhile, the sensitivity, specificity and accuracy will be used as classification performance measurements. Thus, the experimental result and analysis will be discussed in next section.

EXPERIMENTAL RESULT AND ANALYSIS

In this study, the proposed method and standard hexagonal lattice structure (HexaSOM) are trained and tested using 10-fold cross validation. The classification analysis is presented in Table 1 with performance range from 0 to 1 and numbers in bold shows the best value of performance evaluations.

As a result, OctaSOM provides better accuracy than HexaSOM or almost all datasets (Appendicitis, heart, hepatitis, mammographic and Wisconsin dataset). Meanwhile, HexaSOM produce better accuracy, 67.60% than OctaSOM, 66.16% in Pima dataset. The reason is due to the imbalance class in Pima dataset where a negative class is 1.85 times more than positive class (the result is influenced towards the majority class). Furthermore, large gap between feature distributions probably affect the result of Pima dataset.

Table 1. Classification Analysis

Datasets	Methods	Performance Measurements		
		Sensitivity	Specificity	Accuracy
Appendicitis	**HexaSOM**	0.828590147	0.5686321	0.82727273
	OctaSOM	**0.870729**	**0.779827**	**0.87**
Heart	**HexaSOM**	0.688271605	0.7283951	0.72839506
	OctaSOM	**0.776477**	**0.779196**	**0.774074**
Hepatitis	**HexaSOM**	0.488675595	**0.8125149**	0.813188
	OctaSOM	**0.862286**	0.543429	**0.889957**
Pima	**HexaSOM**	**0.676943109**	0.4145954	**0.67608137**
	OctaSOM	0.65486	**0.595955**	0.661641
Mammographic	**HexaSOM**	0.669356734	0.663587	0.67195338
	OctaSOM	**0.750774**	**0.750324**	**0.747396**
Wisconsin	**HexaSOM**	0.721333023	0.4844751	0.72172737
	OctaSOM	**0.978731**	**0.968289**	**0.978213**

CONCLUSION

In this study, we proposed an octagonal-based Self Organizing Map (OctaSOM) for better mapping quality. The aim is to generate various perspectives on SOM's neighborhood lattice structure for classification problems. Hence, the OctaSOM successfully generates promising result in terms of sensitivity, specificity and accuracy particularly on biomedical area.

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