SPIKING NEURONS IN 3D GROWING SELF-ORGANISING MAPS

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ALHAMDULILLAH..

For my beloved mother, father, husband Fadni and my children Azfar and Faris.

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ABSTRACT

In Kohonen's Self-Organising Maps (SOM) learning, preserving the map topology to simulate the actual input features appears to be a significant process. Misinterpretation of the training samples can lead to failure in identifying the important features that may affect the outcomes generated by the SOM model. Nonetheless, it is a challenging task as most of the real problems are composed of complex and insufficient data. Spiking Neural Network (SNN) is the third generation of Artificial Neural Network (ANN), in which information can be transferred from one neuron to another using spike, processed, and trigger response as output. This study, hence, embedded spiking neurons for SOM learning in order to enhance the learning process. The proposed method was divided into five main phases. Phase 1 investigated issues related to SOM learning algorithm, while in Phase 2; datasets were collected for analyses carried out in Phase 3, wherein neural coding scheme for data representation process was implemented in the classification task. Next, in Phase 4, the spiking SOM model was designed, developed, and evaluated using classification accuracy rate and quantisation error. The outcomes showed that the proposed model had successfully attained exceptional classification accuracy rate with low quantisation error to preserve the quality of the generated map based on original input data. Lastly, in the final phase, a Spiking 3D Growing SOM is proposed to address the surface reconstruction issue by enhancing the spiking SOM using 3D map structure in SOM algorithm with a growing grid mechanism. The application of spiking neurons to enhance the performance of SOM is relevant in this study due to its ability to spike and to send a reaction when special features are identified based on its learning of the presented datasets. The study outcomes contribute to the enhancement of SOM in learning the patterns of the datasets, as well as in proposing a better tool for data analysis.

ABSTRAK

Dalam pembelajaran swa-organisasi Kohohen (SOM), proses memelihara topologi peta untuk mewakilkan ciri-ciri data yang sebenar adalah penting. Perwakilan yang salah akan menyebabkan kegagalan dalam mengenalpasti ciri-ciri penting hingga memberi kesan kepada keluaran yang dihasilkan oleh model SOM. Namun, ianya adalah tugas yang mencabar kerana kebanyakan masalah sebenar terdiri daripada data-data yang rumit dan tidak lengkap. Rangkaian Saraf Pakuan (RSP) adalah generasi ketiga rangkaian saraf buatan (RSB) dengan maklumat disalurkan dari satu neuron ke neuron lain melalui pepaku, kemudian diproses untuk menghasilkan tindakbalas sebagai output. Kajian ini menggabungkan saraf pakuan untuk memperkasakan proses pembelajaran SOM. Kaedah yang dicadangkan terbahagi kepada lima fasa utama. Fasa pertama mengkaji isu-isu berkaitan algoritma pembelajaran SOM. Dalam fasa kedua, dataset dikumpul untuk dilatih di fasa ketiga, di mana skema pengkodan saraf diimplementasi bagi proses pengelasan. Seterusnya, dalam fasa keempat, model SOM pakuan direkabentuk, dibangunkan dan dinilai melalui kadar ketepatan pengelasan dan ralat pengkuantuman. Hasil ujikaji menunjukkan model cadangan berjaya menghasilkan keputusan yang baik dengan ralat pengkuantuman yang rendah, untuk memelihara kualiti pemetaan berdasarkan kepada data kemasukan sebenar. Pada fasa terakhir, model swa-organisasi pertumbuhan pakuan tiga dimensi dicadangkan untuk masalah penjanaan semula permukaan dengan meningkatkan pakuan SOM menggunakan struktur peta 3D dalam algoritma SOM bersama mekanisme pertumbuhan grid. Aplikasi saraf pakuan untuk meningkatkan prestasi SOM adalah relevan dalam kajian ini kerana keupayaannya untuk melonjak dan menghantar tindak balas apabila ciri khas dikenalpasti berdasarkan pembelajaran terhadap dataset. Hasil kajian menyumbang kepada peningkatan SOM dalam mempelajari corak dataset, di samping mencadangkan alat yang lebih baik untuk analisis data.

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LIST OF ABBREVIATIONS

1D	-	One Dimensional
2D	-	Two Dimensional
3D	-	Three Dimensional
Acc	-	Accuracy
ANN	-	Artificial Neural Network
AI	-	Artificial Intelligence
AIS	-	Artificial Immune System
ASRA	-	Approximate Surface Reconstruction Algorithm
BCM	-	Bienenstock-Cooper-Munro
BMU	-	Best Matching Unit
CAD/CAM	-	Computer Aided Design / Manufacturing
CCHL	-	Competitive Connection Hebbian Learning
CKSOM	-	Cube Kohonen’s Self-Organizing Maps
COIL20	-	Columbia Object Image Library of 20 objects
CPU	-	Central Processing Unit
CP-ANN	-	Counterpropagation Artificial Neural Networks
CSA	-	Clonal Selection Algorithm
CT	-	Computed Tomography
EEG	-	Electroencephalogram
EPSP	-	Excitatory Postsynaptic Potential
ESOM	-	Extended Self-Organizing Maps
FILT	-	Filtered error signal
FNR	-	False Negative Rate
FPR	-	False Positive Rate
GA	-	Genetic Algorithm
GCS	-	Growing Cell Structures

GHSOM	-	Growing Hierarchical Self-Organizing Maps
GNG	-	Growing Neural Gas
GPA	-	Granulomatosis with Polyangiitis
GPU	-	Graphics Processing Unit
GRF	-	Gaussian Receptive Fields
GSOM	-	Growing Self-Organizing Maps
GSOSM	-	Growing Self Organizing Surface Map
HOAAI	-	Hybrid Optimization Algorithm and An Iterative scheme
HRBF	-	Hermite Radial Basis Functions
ICP	-	Iterate Closest Point
IGA	-	Immune Genetic Algorithm
INST	-	Instantaneous error signal
IP	-	Iterated Power
IPSP	-	Inhibitory Postsynaptic Potential
JHC	-	Jacoby, Hunter and Christian
LLE	-	Locally Linear Embedding
LTD	-	Long Term Depression
LTP	-	Long Term Potentiation
LVQ	-	Learning Vector Quantization
MDS	-	Multidimensional Scaling
MLP	-	Multi-Layer Perceptron
MRI	-	Magnetic Resonance Imaging
NURBS	-	Non-uniform Rational Basis Spline
PCA	-	Principal Component Analysis
PolSOM	-	Polar Self-Organizing Maps
PPoSOM	-	Probabilistic Polar Self-Organizing Maps
PSO	-	Partcle Swarm Optimization
PSP	-	Postsynaptic Potential
Pre	-	Precision
RBF	-	Radial Basis Function
Rec	-	Recall
RC	-	Resistor–Capacitor
ReDSOM	-	Relative Density Self-Organizing Maps

RGB	-	Red, Green and Blue
ROC	-	Receiver Operating Characteristic curve
SAP	-	Spike After Potential
SCD	-	Synthetical Cluster Density
SCOP	-	Structural Classification Of Proteins
SEM	-	Scanning Electron Microscope
SNN	-	Spiking Neural Network
SOM	-	Self-Organizing Maps
SOM-AC	-	Self-organizing Map with modified Adaptive Coordinates
SRM	-	Spike Response Model
STDP	-	Spike Time Dependent Synaptic Plasticity
STSP	-	Symmetrical Traveling Salesperson Problem
SVD	-	Singular Value Decomposition
SVR	-	Support Vector Regression
SWAT	-	Synaptic Weight Association Training
S-SOM	-	Symbolic Self-Organizing Maps
TAIEX	-	Taiwan Weighted Stock Index
TNR	-	True Negative Rate
TPR	-	True Positive Rate
TSEC	-	Taiwan Stock Exchange Corporation
TTOSOM	-	Tree-based Topology-Oriented Self-Organizing Maps
UCI	-	University of California, Irvine
URL	-	Uniform Resource Locator
ViSOM.	-	Visualization Induced Self-Organizing Maps
VLSI	-	Very Large Scale Integration
WeVoS	-	Weighted Voting Superposition
WeVoS-ViSOM	-	Weighted Voting Superposition - Visualization Induced Self-Organizing Maps
WR	-	Weight Recombination
WR PSOM	-	Weight Recombination with Parallel Self-Organizing Maps

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CHAPTER 1

INTRODUCTION

1.1 Overview

The self-organising map (SOM) refers to a data visualisation technique initiated by Professor Teuvo Kohonen (Kohonen, 1995). This technique minimises the dimensions of data through the use of self-organising neural networks. SOM has often been used in the exploratory stage of data analysis, in addition to applications in numerous fields (Corchado, & Baruque, 2012; Shieh, & Liao, 2012; Chaudhary *et al.*, 2015; Ahmad, & Kim, 2015; Natita *et al.*, 2016; Haimoudi *et al.*, 2016; Kuo, & Chen, 2016).

The conventional SOM network is composed of two phases; training and testing. SOM learning occurs during the training phase, while the process of identifying the output occurs during the testing phase. The training samples are generated by transforming the input data into normalised values. Next, the Best Matching Unit (BMU) is identified as the neuron that holds the minimum distance value to the normalised input features. All neurons within the neighbourhood of the BMU are updated so that their values are reflected in the input features. This is the process of SOM learning, wherein the mapping topology is preserved to train the weights to simulate the actual features of the datasets.

Several major issues in the SOM learning algorithm may eventually lead to the failure of identifying of BMU (Mariette, & Villa-Vialaneix, 2016). The first issue refers to the pre-processing of input data for training. Missing important knowledge during data pre-processing can affect the performance of the SOM model. Next, the second issue is misrepresenting the datasets that could unable the identification of potential BMU, and therefore, produce poor mapping topology. Since SOM incorporates an iterative process, the learning process is lengthened and may generate irrelevant outputs (Haimoudi *et al.,* 2016). Thus, in order to ensure the correct interpretation of data, quality measurement is required for the map topology. According to Hamel (2016), quality measurement should cover two aspects: 1) mapping in the input data, and 2) the topological quality of the map. So far, most studies have only covered one aspect; either the input data or the topological structure of the map. This seems to reduce the accuracy of the SOM output.

In order to address these issues, enhancement to the SOM learning algorithm has been proposed in many prior studies. Many researchers have improved the SOM model by modifying the SOM map structures, such as lattice and map dimensions, to preserve the input data in the map topology (Yusob, 2009; Hasan, & Shamsuddin, 2011; Kim, & Ahmad, 2015). Apart from that, improvements were made in SOM learning parameters itself, including initialisation of weight values, learning rate, and neighbourhood function (Fidae *et al*., 2015; Natita *et al.,* 2016). Some studies have integrated other techniques, such as statistical and intelligent approaches as solutions to deal with issues linked with SOM, for example, Particle Swarm Optimisation (Hasan, & Shamsuddin, 2011), Principle Component Analysis (Haimoudi *et al.*, 2016), neural gas (Moazzen, & Tasdemir, 2016; Vergara *et al.,* 2016), and Support Vector Machine (Mudali *et al*., 2016).

These techniques have successfully enhanced the learning capabilities of SOM in vast domain problems. Nevertheless, its operation is time consuming, especially in identifying BMU and map training to generate weight values that represent the real input data. For this reason, a new approach has to be devised by incorporating the advancement in artificial neural network (ANN). Mass (1997) divided ANN into three generations. The first generation is perception, which is used for digital computation. Next, the second generation is based on continuous activation function, for instance, backpropagation and SOM. Lastly, the third generation is spiking neural network (SNN), which is biologically similar to neurons and incorporates spatial information in communication and computation, the actual neuron alike (Ferster, 1995). It also applies pulse coding (spike), wherein neurons receive and send individual pulses (Gerstner, *et al.*, 1999) as the communication method. Due to these characteristics, SNN can be considered as a potential tool for data analysis models (Ponulak, & Kasinski, 2011), apart from being adapted in existing tools (e.g. SOM) to achieve better performance with less intricacy (Sen *et al.*, 2017). The following section describes the application of SNN as a potential solution to address the issues discussed above.

1.2 Problem Background

Only a handful studies have implemented spiking neurons with other neural network models (Bohte *et al.*, 2003; Bohte, 2011; Long, 2011; Ming *et al.*, 2011; Handrich, 2011; Qu *et al.*, 2015; Tavanaei, & Maida, 2015; Gardner, & Gruning, 2016). As such, it is a challenge to extend the spike-based coding to computations due to the lengthy time-scale (Bohte, 2011). At present, SNN is still unclear and the related studies pertaining to natural temporal abilities are insufficient (Li *et al.*, 2017). Most of the prior studies focused on proving SNN as an alternative to conventional models without showing them practically, but instead theoretically via mathematical approach that is not only complicated, but also difficult to interpret (Qu *et al.*, 2015). Besides, no study has evaluated the performance of integration methods in terms of neural coding schemes. In order to investigate the application of spiking neurons in neural network learning, a prior review is presented in the following, particularly concerning the integration of spiking neurons in one of the most popular neural network data analyses; Kohonen's SOMs.

Ruf and Schmitt (1997) displayed how networks of spiking neurons could be used to implement a variation of SOMs in temporal coding. They implemented a variation of Kohonen's learning rule for SOMs within the context of SNNs, in which extremely promising outputs were attained. The typical self-organisation of topology-preserving behaviour was observed for a wide range of parameters. The proposed model was capable of rapidly determining the winner among the locally competing neurons by using lateral excitation and inhibition.

Ruf and Schmitt (1998) proposed a mechanism for unsupervised learning in networks of spiking neurons, which was based on the timing of single firing events. This approach offers the basis for fast implementations in pulse very large-scale integration (VLSI).

Pham *et al.,* (2007) proposed a self-organising delay adaptation SNN model to cluster control chart patterns. Similar to Kohonen, they employed the SOM, except that the output layer neurons detected the spiking neurons with temporal coding SNN and Hebbian-based rule. The trained network obtained an average clustering accuracy of 96.1% for previously unseen data, which seemed better than that of the original Kohonen.

Ming *et al.,* (2011) suggested a hybrid model of SOM with modified adaptive coordinates (SOM-AC) and SNN for multivariate spatial and temporal data visualisation and classification. They used the Izhikevich model and the one-dimensional (1D) encoding, which was used by Belatreche *et al.,* (2006) for neural coding method. Empirical studies of the proposed model using synthetic and benchmarking datasets yielded promising classification accuracy and intuitive rich visualisation, which can be used not only for spatial data, but also for temporal data.

1.3 Problem Statement

Pre-processing of the input data from datasets for training and BMU identification are important features in SOM learning. Nonetheless, they appear to be challenging for researchers as most real problems are comprised of complex and insufficient data (Haimoudi *et al.*, 2016). Misinterpretation of training samples could hinder BMU identification, which may affect the outcomes generated by the SOM model. In SNN, the neural coding scheme is typically used to encode information from real data into spike times, which are present in more reliable forms in neuron simulation. Some recent studies have suggested SNN as a potential alternative solution to enhance learning due to its superiority in capturing the internal relationship of the neurons. However, they have yet to be practically proven against real world problems (Qu *et al.*, 2015).

As such, this study focused on embedding spiking neurons in SOM learning for data exploration and analyses, so as to identify patterns and correlations between input data. Hence, the primary research question for this study is as follows:

Can spiking SOM optimise the SOM learning process for better representation of the data in mapping and topology of the input neurons?

This leads to the following secondary research questions:

i) How can the spiking neurons be integrated with SOM learning parameters to enhance its performance?
ii) How can the BMU of the spiking SOM model be optimised in the topology map?
iii) How effective is the proposed Spiking SOM in comparison to other spiking models?

1.4 Aim of the Research

This research proposes a spiking neural model to optimise the BMU of SOM learning by preserving the map topology for better data representation.

1.5 Objectives of the Research

In order to achieve the aim of the study, the following objectives have been outlined:

i) To propose integrated spiking neurons in Kohonen's SOM learning algorithm.

ii) To optimise the spiking SOM model based on the BMU.

iii) To investigate the effectiveness of the proposed spiking SOM in comparison to other spiking models.

iv) To develop and to integrate the proposed spiking SOM in surface reconstruction.

1.6 Scope of the Research

i) The proposed algorithm was tested on several standard datasets (UCI datasets).

ii) Two neural coding schemes were used in preparing the input features for the spiking SOM:

   a) Gaussian Receptive Fields, and
   b) 1D Coding.

iii) Evaluation of the proposed method was based on the performance comparison with other spiking models and conventional SOM models.

1.7 Significance of the Research

This study proposes the integration of spiking neurons in SOM learning algorithm for the data analysis process. The application of SNNs to enhance the performance of SOM in analysing and identifying special features in the datasets appear to be relevant in this study due to its ability to spike and to send reaction special features identified based on its learning of the presented datasets. The study outcomes contribute to the enhancement of SOM in learning the patterns of the datasets, as well as to propose an improvised tool for data analysis.

1.8 Research Methodology

Table 1.1 presents the summary of the elaborated approach in formulating the research methodology. Initially, the research issues were identified and a solution for each issue was proposed. The solutions were driven by the objectives specified in Section 1.5 of this chapter.

Table 1.1: The outline of research issues and the research objectives

Issues	Objective	Solution in Chapter
Pre-processing of input data for SOM training (Haimoudi *et al.*, 2016)	To propose an integration of spiking neurons in Kohonen's SOM learning algorithm.	4
Identification of BMU (Mariette, & Villa-Vialaneix, 2016)	To optimise the spiking SOM model based on the BMU.	4
Quality Measurement of Map Preservation (Hamel, 2016)	To investigate the effectiveness of the proposed spiking SOM with other spiking models.	4
Unorganised point cloud data (Forkan, 2009)	To develop and to integrate the proposed spiking SOM in surface reconstruction.	5

This study was conducted in phases, as described in Chapter 3. The phases are as follows:

i) Phase 1: Problem identification that focused on identifying the research problems by investigating issues related to Kohonen's SOM learning algorithm.

ii) Phase 2: Data collection process and preparation of the data for the experiment in order to evaluate the performance of the proposed solution.

iii) Phase 3: Neural coding scheme for data representation process was implemented in the SOM model to prepare the datasets for the classification task. In this phase, the spiking SOM model was designed and developed.

iv) Phase 4: The proposed solution was designed and developed for surface reconstruction problem by enhancing the spiking SOM using 3D map structure in the SOM algorithm with the growing grid mechanism. Concurrently, a few SOM models were proposed.

v) Models designing and development were divided into three sub-phases. Every sub-phase consisted of model formulation, development, and evaluation. In model formulation, the design and the requirement for each model were defined. The model development refers to the process of constructing the models. In model evaluation and validation process, the models were trained and tested through experiments using selected datasets for surface reconstruction.

vi) Phase 5: The experimental outcomes were analysed and are reported.

1.9 Organisation of the Thesis

This thesis is divided into 6 chapters. Chapter 1 introduces the overview of the study, the problem background, and the problem statement. Additionally, the aim and the objectives of the study are introduced based on the research questions. Finally, the process of conducting the study and its significances for the research are presented.

Chapter 2 presents the literature review of SOM learning algorithm, an overview of SNN, and several issues concerning the learning process for both neural networks. The chapter ends with a case study of surface reconstruction problems and the existing methods in dealing with the issues portrayed in the case study.

Chapter 3 includes the research methodology, the framework of the proposed study, and the details of each phase conducted in the study.

Chapter 4 explains in detail the data representation process using neural coding schemes and BMU identification adapted from SNN.

Chapter 5 describes the proposed model for the case study, i.e. spiking neurons in 3D-growing SOMs. The experimental results are also discussed in this chapter, including several reports from the analyses carried out. Finally, the conclusion and possible future works are described in Chapter 6.

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