PARAMETER OPTIMIZATION OF EVOLVING SPIKING NEURAL NETWORK WITH DYNAMIC POPULATION PARTICLE SWARM OPTIMIZATION

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“My dearest Lily, Addy, mama, ayah and family”

This is for all of you

DEDICATION

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ABSTRACT

Evolving Spiking Neural Network (ESNN) is widely used in classification problem. However, ESNN like any other neural networks is incapable to find its own parameter optimum values, which are crucial for classification accuracy. Thus, in this study, ESNN is integrated with an improved Particle Swarm Optimization (PSO) known as Dynamic Population Particle Swarm Optimization (DPPSO) to optimize the ESNN parameters: the modulation factor (*Mod*), similarity factor (*Sim*) and threshold factor (*C*). To find the optimum ESNN parameter value, DPPSO uses a dynamic population that removes the lowest particle value in every pre-defined iteration. The integration of ESNN-DPPSO facilitates the ESNN parameter optimization searching during the training stage. The performance analysis is measured by classification accuracy and is compared with the existing method. Five datasets gained from University of California Irvine (UCI) Machine Learning Repository are used for this study. The experimental result presents better accuracy compared to the existing technique and thus improves the ESNN method in optimising its parameter values.

ABSTRAK

Rangkaian Neural Pakuan Berevolusi (ESNN) digunakan secara meluas dalam masalah mengklasifikasi. Walau bagaimanapun, ESNN seperti mana rangkaian saraf lain tidak mampu untuk mencari nilai optimum parameter sendiri, untuk ketepatan klasifikasi. Oleh itu, dalam kajian ini, ESNN digabungkan dengan Pengoptimuman Kelompok Partikel (PSO) yang lebih baik yang dikenali sebagai Pengoptimuman Kelompok Partikel Dinamik (DPPSO) untuk mengoptimumkan parameter ESNN: faktor modulasi (*Mod*), faktor kesamaan (*Sim*) dan faktor ambang (*C*). Untuk mencari nilai parameter ESNN optimum, DPPSO menggunakan populasi yang dinamik yang menghilangkan nilai zarah terendah dalam setiap lelaran yang telah ditentukan sebelumnya. Penyepaduan ESNN-DPPSO memudahkan pencarian pengoptimuman parameter ESNN semasa proses latihan. Analisis prestasi diukur dengan ketepatan klasifikasi dan dibandingkan dengan kaedah yang sedia ada. Lima dataset yang diperoleh dari Repositori Pembelajaran Mesin *University of California Irvine* (UCI) digunakan untuk kajian ini. Hasil kajian menjelaskan ketepatan yang lebih baik berbanding dengan teknik sedia ada dan dengan itu meningkatkan kaedah ESNN dalam mengoptimumkan nilai parameternya

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Mod	-	Modulation factor
Sim	-	Similarity factor
C	-	Threshold
PSP	-	Pre-synaptic neuron

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CHAPTER 1

INTRODUCTION

1.1 Overview

Neural networks have influence many researchers in solving problems related to classification, speech recognition and prediction. Neural network is dependent on its parameter to establish the best result. Neural networks, inspired by the human brain, are gaining popularity nowadays due to their capability in solving various problems. The prominent model of the neural network is the Artificial Neural Network (ANN); a group of processing components in a collective network which resembles the features of a biological neural network (Sedghi *et al*., 2014). In ANN, training a network is the process of varying the weights in between layers of a network to obtain the preferred output (Gautam, 2016). The Mcculloch and Pitts Artificial Neuron Model (MPAN) introduced in 1943 is the basic form of the neural network (Narain *et al.*, 2007).

The Spiking Neural Network (SNN) is the recent and in the third generation of neural network. Evolving Spiking Neural Network (ESNN) is a well-known SNN architecture. ESNN has latest spiking neuron that evolves (Hamed, 2012). ESNN has the ability to fast learning where it studies a new pattern that comes from the incoming data in one pass-mode that will form a new network without retraining (Dhoble *et al.*, 2012). ESNN is widely applied to solve classification issue (Hamed, 2012; Saleh *et al.*, 2014; Dora *et al.*, 2018), prediction problem (Arya *et al.*, 2016) and pattern recognition (Wang *et al.*, 2015).

ESNN is useful for data processing; however, the main issue arises is in deciding the optimum parameter values for a dataset (Saleh *et al., 2014*). For every neural network there are parameters involved and some approaches are employed for parameter setting such as manual tuning or an automated process using an optimizer (Silva *et al.,* 2014). The parameter refinement in ESNN is important since its influence the output result. Thus, an optimizer algorithm helps ESNN to find its parameter optimum value. There are many types of optimizer algorithm such as Dynamic Population Particle Swarm Optimization, Genetic Algorithm, Evolutionary Algorithm, Particle Swarm Optimization and much more. Hence, a new approach is proposed in this research to solve the data classification problem using an Evolving Spiking Neural Network (ESNN) with Dynamic Population Particle Swarm Optimization (DPPSO) as an optimizer

1.2 Problem Background

Spiking Neural Network (SNN) falls into the third generation of Artificial Neural Networks (ANN). The Evolving Spiking Neural Network is one of the prominent SNN architecture. This model is believed to be an auspicious technique due to its simplicity, a competent neural model and rapid one-pass learning. However, according to Saleh *et al.* (2014) the fundamental problem encountered in ESNN is that the manual tuning of the parameters needs to be done since deciding the optimum value for the parameters for a dataset is crucial.

ESNN consist of three parameters where its value can be changed accordingly, these are known as the modulation factor (*Mod)*, the threshold (*C)* and the similarity factor (*Sim).* According to Hamed *et al.* (2009) similar to other neural network models, ESNN also needs the right parameter mixture for the network execution. Since these parameters influence the segregation outcome, the ESNN capability and is reliant on data to be categorized, further improvement of the model is necessary in terms of optimizing its parameter (Schliebs *et al.*, 2010).

ESNN model is unable to find its own parameter optimal value. Therefore, an optimizer algorithm helps the ESNN to optimize its parameter. Several ESNN integrated with an optimizer algorithm has been done previously to cater the issue (Schliebs *et al.,* 2009; Hamed *et al.,* 2009; Saleh *et al.,* 2014). The previous works demonstrate an improvement in ESNN performance. However, there are many potential optimizers that are worth explored in order to solve this issue more efficiently. One of the optimizer algorithms notable by many to solve parameter setting is Particle Swarm Optimization (He *et al*., 2017; Harrison *et al.,* 2017; Zhu *et al.*, 2017).

PSO was introduced by Kennedy and Eberhart and was inspired by the nature of bird flocking (Kennedy, 2010; Eberhart and Kennedy 1995). PSO is easy to apply, has less parameter to regulate and proven to be robust in resolving optimization issue (M'hamdi *et al.*, 2016). However, according to Saxena *et al*., 2015, the PSO has disadvantages such as trap in local optima. Thus, recent studies have shown that PSO need improvement to enhance the quality of the objective function by manipulating the particle population and known as Dynamic Population Particle Swarm Optimization (DPPSO) (M'hamdi *et al.,* 2016; Saxena *et al.,* 2015; Leong and Yen, 2008).

DPPSO has the ability to dynamically manipulate its population to find the best fitness value. The manipulation of the DPPSO population can increase or decreasing. Previous work has proven that by removing or adding a single particle can improve the performance of the algorithm (Soudan and Saad, 2008; Sun *et al*., 2007; Tundong *et al*., 2012). However, according to Soudan and Saad, 2008, iteratively decreasing the population size is better in terms of accuracy. Previous work has shown that the dynamic PSO is used for parameter estimation (Liu, *te al.*, 2017; M'hamdi *et al.*, 2016; Khan *et al.,* 2016; He *et al*., 2017). Thus, DPPSO is a promising candidate to integrate with ESNN to automate the parameter setting.

1.3 Problem Statement

ESNN architecture that has spiking neuron, one pass learning where the ability to process data is faster since it eliminates retraining data. It has shown promising result in data processing (Saleh *et al.*, 2014). However, similar to other neural network, ESNN needs parameter refining and incapable to find its parameter optimum value (Silva, *et al.,* 2014). The process of parameter setting in manual tuning by trial and error approach is a challenging task. Based on previous work by (Hamed, 2012; Saleh *et al.,* 2014, Schliebs and Kasabov, 2013) shows that ESNN model is integrated with an optimizer algorithm to enhance its performance result. However, no previous work has applied dynamic population PSO with ESNN model to solve classification problem. Thus, for this research, an integration of dynamic population PSO (DPPSO) with ESNN is proposed in resolving classification issue.

1.4 Aim of Study

The aim of this study is to enhance the Evolving Spiking Neural Network learning for classification problems with the help of the parameter optimization technique called new Dynamic Population Particle Swarm Optimization algorithm.

1.5 Research Question

The research questions to address the research objective are as follows:.

i) How to optimize ESNN for best performance in solving classification problem?

ii) How to enhance PSO as a new and effective Evolving Spiking Neural Network parameter optimizer?

iii) What is the optimum value of ESNN parameters?

1.6 Research Objectives

The objectives of the study are as follows:

i) To develop an integrated ESNN and DPPSO model to solve classification problem.
ii) To introduce new dynamic-population-PSO (DPPSO) as an effective parameter optimizer for ESNN.
iii) To discover the optimum values of ESNN parameters

1.7 Research Scope

In this research, the following scope will be covered to achieve the stated goals:

i) The proposed algorithm is to solve classification problems.
ii) The proposed architecture will optimize three ESNN parameters namely the Modulation Factor, Similarity Factor and the Threshold.
iii) Testing of the algorithm will use five benchmark datasets, specifically the Iris, Breast Cancer, Pima Indian Diabetes, Heart and Wine datasets from UCI Machine Learning.
iv) Performance will be measured based on classification accuracy as implemented by other researchers in the same field.

1.8 Research Significance

The significance of the research is as follows. Firstly, utilize DPPSO with evolving spiking neural network to optimize ESNN parameter. The ESNN model is dependent on parameter tuning. Thus, an optimizer is needed to help automate the process of determining the ESNN's parameter optimum value (Saleh *et al.*, 2014). The proposed DPPSO implement dynamic population where a lowest fitness particle is removed in every 20% of the cycle. This in returns will create a population that has only good fitness value. Thus, an optimum value for ESNN parameter can be selected easily by using DPPSO.

Secondly, DPPSO has not been applied yet to optimize ESNN parameter. Previous studies using an optimizer algorithm for the evolving spiking neural network include the use of the Differential Evolution Algorithm (Saleh *et al.*, 2014), Particle Swarm Optimization (Hamed *et al.*, 2011), Rank Order Learning (Dhoble *et al.*, 2012) and Quantum Inspired SNN (Schliebs *et al.*, 2010).

1.9 Research Outline

This part describes the organization of the research outline:

Chapter 1: This chapter presents the introduction to the research that includes the introduction, problem background, problem statement and the aim of the study, objectives, research scope and the research significance.

Chapter 2: This chapter provides the literature review relating to the research. This comprises the overview of the neural network which includes types of neural network, the architecture and the applications of the neural network.

Chapter 3: This chapter describes the research methodology of the research. It presents the research framework, data description and algorithm overview of the Evolving Spiking Neural Network and Dynamic Population Particle Swarm Optimization.

Chapter 4: This chapter provides the results of the proposed ESNN-DPPSO for classification issue. Also, the empirical analysis of the existing optimization technique is discussed.

Chapter 5: This chapter presents the conclusion and future work.

1.10 Publication

Throughout the two years of study, the following publications have been accepted to be published:

v) Said, N. N. M., Hamed, H. N. A., and Abdullah, A (2017). The Enhancement of Evolving Spiking Neural Network with Dynamic Population Particle Swarm Optimization. *Communications in Computer and Information Science*, 752, 95-103. Springer. (Scopus indexed)

vi) Said, N. N. M., Hamed, H. N. A., and Abdullah, A (2017). The Integration of Evolving Spiking Neural Network with Dynamic Population Particle Swarm Optimization. Accepted in ICEEI2017 and to be published in Scopus indexed journal (IJEECS or IJEEI).

1.11 . Summary

This chapter first describes the introduction to the research. Next, the problem background to the research is presented. Then, the aim of the study is described and the objectives of the research are explained. Later, the scope and also the significance of the study are addressed. The research outlines are then further reviewed. The next chapter will present the literature review relating to the research.

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