BACTERIAL FORAGING OPTIMIZATION ALGORITHM FOR NEURAL NETWORK LEARNING ENHANCEMENT

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A dissertation submitted in partial fulfillment of
requirements for the award of the degree of
Master of Science (Computer Science)

Faculty of Computer Science and Information Systems
Universiti Teknologi Malaysia

JULY 2011

To my beloved mother, to the spirit of my father, to my big brother Yahya ,
to my beloved brothers, to my beloved sisters, to my beloved wife ,
to our children Ahmed and Rana.

ACKNOWLEDGEMENT

In the Name of Allah, Most Gracious, Most Merciful

Alhamdulillah, it is with Allah S.W.T will that finally I get to finish this dissertation. In completing this dissertation, I was contacting many people and they have contributed toward my understanding. First of all, I wish to express my sincere appreciation to my supervisor, Associate Professor Dr. Siti Zaiton Mohd Hashim for her attention and generous help throughout the length of this study. I am very thankful for her kind guidance since the first day of this study. I am also very thankful to my co-supervisor, Professor Dr. Siti Mariyam Hj Shamsuddin for her advices and motivation. Not forgotten to my evaluators, Dr. Roselina Salehuddin, Dr. Azlan Mohd Zain and Dr Erne Nazira Bazin , I am also grateful for their helpful suggestions.

A special thanks to my family members, my waif, my dearest sisters and brothers, thanks a lot for all the everlasting support, love and care along my journey of life.

Last but not least, I am very thankful to all the lectures that have been giving me good knowledge, high motivation and self-esteem, and made my experience of learning here worthwhile. My overwhelming gratitude to all my friends that have been together with me, thanks for all the care, concern and love. The sweet memory with you all will never fade away and will be cherished it forever.

ABSTRACT

Backpropagation algorithm is used to solve many real world problems using the concept of Multilayer Perceptron. However, main disadvantages of Backpropagation are its convergence rate is relatively slow, and it is often trapped at the local minima. To solve this problem, in literatures, evolutionary algorithms such as Particle Swarm Optimization algorithm has been applied in feedforward neural network to optimize the learning process in terms of convergence rate and classification accuracy but this process needs longer training time. To provide alternative solution, in this study, Bacteria Foraging Optimization Algorithm has been selected and applied in feedforward neural network to enhance the learning process in terms of convergence rate and classification accuracy. One of the main processes in Bacteria Foraging Optimization algorithm is the chemotactic movement of a virtual bacterium that makes a trial solution of the optimization problem. This process of chemotactic movement is guided to make the learning process of Artificial Neural Network faster. The developed Bacteria Foraging Optimization Algorithm Feedforward Neural Network (BFOANN) is compared against Particle Swarm Optimization Feedforward Neural Network (PSONN). The results show that BFOANN gave better performance in terms of convergence rate and classification accuracy compared to PSONN.

ABSTRAK

Algoritma Rambatan Balik (BP) digunakan untuk menyelesaikan banyak masalah dunia nyata menggunakan konsep Perseptron Pelbagai lapisan. Namun, kelemahan utama algoritma BP adalah kadar penumpuan yang lambat, dan sering terperangkap di lokasi minimum tempatan. Untuk mengatasi masalah ini, dalam literatur, algoritma evolusi seperti Pengoptimuman Partikel Berkelompok (PSO) telah dilaksanakan dalam rangkaian saraf tiruan suapan depan untuk mengoptimumkan proses pembelajaran dari sudut kadar penumpuan dan ketepatan klasifikasi namun proses ini memerlukan masa latihan yang lama. Untuk memberikan penyelesaian alternatif, dalam kajian ini, algoritma pengoptimuman bakteria carian (BFO) telah dipilih dan diterapkan pada jaringan saraf tiruan suapan depan untuk meningkatkan proses belajar dari segi kadar penumpuan dan ketepatan klasifikasi. Salah satu proses utama dalam algoritma BFO adalah gerakan *chemotactic* dari bakteria maya yang membuat percubaan penyelesaian bagi masalah pengoptimuman. Proses gerakan *chemotactic* dipandu untuk menyelesaikan masalah Jaringan Neural buatan (ANN) dengan lebih cepat. Gabungan algoritma BFO dan ANN (BFOANN) yang dibangunkan dibandingkan dengan PSO dan ANN (PSONN). Keputusan kajian menunjukkan bahawa BFOANN memberikan hasil yang lebih baik dari sudut konvergensi dan ketepatan klasifikasi dibandingkan dengan PSONN.

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LIST OF SYMBOLS

S	-	Number of bacteria
P	-	Dimension of the search space
Nc	-	Number of chemotactic steps
Ns	-	Limits the length of a swim
Nre	-	The number of reproduction steps
Ned	-	The number of elimination-dispersal events
Ped	-	The probability that each bacteria will be eliminated/dispersed
C	-	Run length unit

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
NN	-	Neural Network
BP	-	Backpropagation
GA	-	Genetic Algorithm
PSO	-	Particle Swarm Optimization
MLP	-	Multilayer Perceptron
SI	-	Swarm Intelligence
BFOA	-	Bacterial Foraging Optimization Algorithm
GANN	-	Genetic Algorithm Backpropagation Neural Network
PSONN	-	Particle Swarm Optimization Feedforward Neural Network
BFOANN	-	Bacterial Foraging Optimization Algorithm Feedforward Neural Network
ELM	-	Extreme Learning Machine
DE	-	Differential evolution
HAP	-	A Hybrid of Artificial Fish Swarm Algorithm and Particle Swarm Optimization for Feedforward Neural Network Training

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CHAPTER 1

INTRODUCTION

1.1 Overview

Artificial Neural Network (ANN) is a model of information processing simulated by the biological nervous system. Feedforward Neural Network (FFNN) has been commonly used in several fields such as control applications (Vemuri, 1993), dynamic problems (Massimo, 2007) and power systems (Haque and Kashtiban, 2005). This is because ANN has the ability to closely approximate unknown function to each degree of desired accuracy (Zhang and Wu, 2008). There are many calculations, which are very complex, nonlinear and parallel that could be solved by ANN. However, many applications have been improved by the neural network algorithm and many of them are on predicting future events based on historical data. ANN is a power face that consists of network that processes many things like learning and adaptation. Furthermore, ANN can be very efficient for solving problems in pattern recognition, scientific classification, function approximation, the analysis of time series data, and control (Long and Gupta, 2005)

The main purpose of ANN is the capacity of the network on learning from its surroundings and improves the performance of this model during the process of learning (Haza, 2006). Learning is an operation of the optimization of the neuron's weights and biases values of ANN until a certain criterion is met. The classification of fixed input data patterns to certain outputs is the main objective of training method. There are many algorithms that are used for training a neural network such as the back propagation algorithm (BP) (Alsamdi et al., 2009), Genetic Algorithm (GA) (Khan et al., 2008) and Particle Swarm Optimization (PSO) (Haza, 2006). BP algorithm is applied to train the neural network for associative learning or supervised. Supervised learning algorithm requires direct and complete desired answers like a feedback; that mean the value of target or the planned outputs. During training, weights of the network and biases are optimized to new weights that are used to get the target value of this network. Some disadvantages of this algorithm are poor local optimal convergence and poor performance even on simple problems (Zhang and Wu, 2008).

There are Evolutionary Algorithms (EAs) that relate to learning enhancement of ANN such as Genetic Algorithm (GA) (Khan et al., 2008), Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995a), and Artificial Fish Swarm Algorithm (Zhang et al., 2006). These algorithms are used to optimize the weights and biases of ANN to obtain the optimal performance of ANN with higher accuracy.

Recent development shows that Bacterial Foraging Algorithm is utilized to solve optimization-related problems (Passino, 2002). To perform social foraging, animals request communication capabilities and over a period of time it increases advantages that can develop the sensing capabilities of the bacteria. This helps the bacteria to get priority to obtain a larger prey or food. Furthermore, each bacterium could obtain good protection from predators (Kim and Abraham, 2007). Bacteria Foraging Optimization Algorithm (BFOA) has been widely used for global optimization (Shen et al., 2009). BFOA is used to solve many optimization problems such as Adaptive Tuning of PID Controllers by BFOA for Multivariable System (Kim and Cho, 2005). This technique can also potentially produce effective solutions to very large scale problems. However, BFOA is used to solve a highly non-linear and non-convex problem which includes Optimal Power Flow solution (Tripathy et al., 2006). Based on this, BFOA is selected to be used in optimizing neural network learning.

1.2 Problem Background

Artificial Neural Network (ANN) is a resultant of a biological brain neuron that is a method to obtain patterns of data. The primary benefit of ANN is its ability to identify patterns in data, while ANN consists of interconnected nodes whose operation as a total is based on the parallel processing power of the nodes gained through their connection strengths. The main disadvantages of ANN classifier are its slow convergence, and it is often trapped at the local minima (Mashinchi, 2007).

The artificial neurons are organized in layers, and send their signals “forward”, and then the errors are propagated backwards. To improve the performance of Neural Network, the optimization algorithms, such as GA (Khan et al., 2008), PSO (Gudise et al., 2003), and BP (Aal-Yhia and Sharieh, 2007) are used. These algorithms train the neural network to obtain a good error convergence, a convergence time, and the classification accuracy.

The main goal of training ANN is to obtain a set of weights that will be optimized by an optimization algorithm. The process of training remains until an acceptable error is achieved by the best one (a particle, a chromosome, a bacterium) or computational limits are exceeded. When a process is finished, the weights are used to calculate the classification for the training patterns. The same set of weights is used to test the network by using the test patterns in order to get the test error (Al-kazemi and Mohan, 2002).

Backpropogation algorithm (BP) is the most common technique in Neural Network learning. It is used to solve many real world problems as a consequence of using the concept of Multilayer Perceptron (MLP) training and testing. The main disadvantages of BP are its relatively slow convergence rate, and it is being trapped at the local minima (Haza, 2006).

Throughout the years, there are many studies in optimizing ANN using different kinds of methods (Ileană et al., 2004). Particle Swarm Optimization Feedforward Neural Network (PSONN) and Genetic Algorithm Backpropagation Neural Network (GANN are two of the well-known Neural Networks optimizing techniques. GA has attracted a great attention in the ANN where it is used to train FFNN through identifying unimportant neuron and delete those neurons to produce a compact structure. However, GA works with a population of solutions to seek many local minima that increase the likelihood of finding global minimum (Er and Liu, 2009). There are many strengths and weaknesses of BP algorithm and the optimization algorithms such as PSO, GA and BFOA. Table 1.1 defines the strengths and weaknesses of these algorithms.

Table 1.1: A Comparison of PSO, GA, BFOA, and BP

Algorithm	Strengths	Weaknesses
BP	1. The gradient-based method has the advantage of being computationally very efficient. 2. BP is designed to reduce an error between the actual output and the desired output of the network in a gradient descent manner (Alsamdi et al., 2009).	1. BP has many disadvantages such as easily falling into the local minimum point, low rate of convergence and weak global search capability (Li et al., 2010) 2. BP has many weaknesses in training ANN when dealing with huge dataset. BP could not avoid the local minima.
PSO	1. PSO is Implemented easily on ANN and there are few parameters to change. 2. PSO is implemented in many areas efficiently (AbdulSttar, 2008).	1. PSO implemented using many iterations cannot recognize the nonlinear system with higher accuracy with other algorithms. 2. The PSO algorithm required too much training time. The training process is often not efficient enough.
GA	1. GA basically is a parallel scheme. It can explore the whole dimensional space at once. 2. GA is suited to solve the problems where the space of all possible solutions is huge and search in the suited amount of time. 3. GA has a good performance to solve the problems where its	1. GA sometimes unable to find a solution to the problem, or may solve the problem incorrectly. 2. GA may not be exploring the solution space to find the suited solutions. 3. The GA convergences early.

Algorithm	Strengths	Weaknesses
	fitness function is continuous, and it changes over time (AbdulSttar, 2008).	
BFOA	1. BFOA explores the whole dimensional space of the problem, and it has strong connections between cell and cell by using the signals. 2. BFOA is easily implemented in many complex areas. 3. BFOA may be able to deal with huge data and find the best solution within a short time. 4. BFOA may be able to solve the problem of local minima and global minima efficiently. 5. BFOA may be able to obtain the optimum solution with high accuracy at the short time and little iteration.	1. If the number of bacteria is big then it results to more delay and complexity. 2. The reproduction phase of bacteria aims at fast convergence suitable in the static environment but it is unsuitable in the dynamic environment (Bakwad et al., 2010).

There are some problems in ANN learning such as the difference between the target output of ANN learning and the actual output. Many researchers worked to optimize the performance of ANN learning to obtain the optimal performance. Many optimization algorithms are used to optimize ANN for enhancing the error convergence and obtaining the good accuracy of ANN. BP algorithm represents the main weakness of ANN this research looks into utilizing BFOA to optimize ANN structure to obtain better performance.

1.3 Problem Statement

There are many elements to be considered in Artificial Neural Network (ANN), such as the number of input, hidden and output nodes, bias, minimum error and the type of activation/transfer function. All these elements will influence the convergence of ANN learning. There are some algorithms such as PSO and GA that have been used to determine some parameters and supply the best pattern of weight in order to enhance the ANN learning.

In this study, the Swarm Intelligence technique called Bacteria Foraging Optimization Algorithm (BFOA) is applied to enhance the Feedforward Neural Network learning and evaluate the performance of BFOA on the convergence rate and the convergence speed.

The hypothesis of this research can be stated as:

How efficient is the BFOA for neural network learning enhancement compared to other optimization techniques such as PSO?

1.4 Research Aim

This research aims to investigate the efficiency of the BFOA in optimizing the weights of the neural network so that the learning is further enhanced to improve the accuracy and convergence of neural networks with minimal error.

1.5 Objectives of the Research

In this study, there are three objectives identified:

1. To explore and implement BFOA and adapt it with neural network.
2. To propose and apply BFOA to optimize the weights and bias in neural network to enhance ANN learning.
3. To compare the results between BFOANN and PSONN in terms of convergence rate and classification accuracy percentage.

1.6 Scopes of the Research

1. The datasets used to analyze the performance of proposed method are XOR, Balloon, Cancer, Heart and Ionosphere.
2. The performance is measured in terms of network convergence and classification percentage by using BFOANN program.

1.7 Contribution of Research

The performance of BFOA-based neural network and PSO-based neural network is analyzed; as a result we can decide which method is better for neural network learning. This is important to identify the best technique to be used in real world application.

1.8 Organization of Report

This report consists of six chapters. In Chapter one, the introduction of the study, problem background, problem statement, research aim, objectives, scope and contribution of this research are presented. Chapter two offers literature reviews on ANN, BP, GA, PSO and BFOA and related work. In chapter three, the methodology of BFOANN is offered. It discusses the main process of BFOANN model. Chapter four shows the architecture of ANN by using five datasets. It explains the flowchart of BFOANN model and shows how BFOA implements with ANN. Chapter five shows the results of implementing BFOA with ANN and PSO with ANN using five datasets. The results are explained and compared with both algorithms. Furthermore, it validates the performance of both algorithms using N-Cross-Validation. Finally, chapter six presents the conclusion and suggestions for the future work.

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