LEARNING ENHANCEMENT OF RADIAL BASIS FUNCTION NEURAL NETWORK WITH HARMONY SEARCH ALGORITHM

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"To my beloved parents, wife and children, thank you for your endless support, encouragement, patience, and understanding and to my lecturers and friends for their respect and support. May ALLAH always revive our sweet memory"

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ABSTRACT

Training Radial Basis Function (RBF) neural network with Particle Swarm Optimization (PSO) was considered as a major breakthrough, that overcome the stuck to the local minimum of Back Propagation (BP) and time consuming and computation expensive problems of Genetic Algorithm (GA). However, PSO proved some problems to achieve the goal, i.e., it converged too fast so that it stuck to the local optimum. Furthermore, particles may move to an invisible region. Therefore, to realize the enhancement of the learning process of RBF and overcome these PSO problems, Harmony Search Meta-Heuristic Algorithm (HSA) was employed to optimize the RBF network and attain the desired objectives. The study conducted a comparative experiments between the integrated HSA-RBF network and the PSO-RBF network. The results proved that HSA increased the learning capability of RBF neural network in terms of accuracy and correct classification percentage, error convergence rate, and less time consumption with less mean squared error (MSE). The new HSA-RBF model provided higher performance in most cases and promising results with better classification proficiency compared with that of PSO-RBF network.

ABSTRAK

Latihan Asas Fungsi Jejari jaringan saraf bersama serpihan kumpulan optimum telah diambil kira sebagai penemuan yang besar yang dapat mengatasi sekatan kepada minimum tempatan penyebaran belakang serta penggunaan masa dan masalah pengiraan algoritma genetic yang mahal. Walau bagaimana pun serpihan kumpulan optimum telah membuktikan sesetengah masalah untuk mencapai sasaran contohnya penumpuannya terlalu laju supaya ia tersekat pada optimum tempatan. Dalam pada itu serpihan mungkin beralih kepada bahagian tak dapat dilihat. Oleh itu, untuk memahami penambahbaikan proses pembelajaran Latihan Asas Fungsi Jejari dan mengatasi masalah serpihan kumpulan optimum, Pencarian Algoritma Harmoni Meta-Heuristik dijalankan untuk optimumkan rangkaian Latihan Asas Fungsi Jejari dan mencapai objektif yang disasarkan. Kajian ini di jalankan melalui perbandingan eksperimen di antara gabungan jaringan Pencarian Algoritma Harmoni Meta-Heuristik dan Latihan Asas Fungsi Jejari serta gabungan serpihan kumpulan optimum dan Latihan Asas Fungsi Jejari. Keputusan menunjukkan Pencarian Algoritma Harmoni Meta-Heuristik menambahkan keupayaan jaringan saraf Latihan Asas Fungsi Jejari dari segi ketepatan dan peratusan klasifikasi, kesalahan kadar penumpuan, dan pengurangan masa dengan pengurangan kesalahan purata persegi (MSE). Penghasilan gabungan Pencarian Algoritma Harmoni Meta-Heuristik dan Latihan Asas Fungsi Jejari ini menyediakan prestasi yang lebih tinggi di dalam kebanyakan kes serta menjanjikan keputusan yang lebih baik kecekapan klasifikasi berbanding dengan gabungan jaringan serpihan kumpulan optimum dan Latihan Asas Fungsi Jejari.

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INTRODUCTION

1.1 Introduction

Artificial neural network's mimicking ability to human talent and their similarity to the structure of the neurons of the human brains attracted the eyes of many researchers due to its unparalleled properties, such as adaptability, learning and generalization capability (Kulluk *et al.*, 2012). Basically the principles of the Artificial Neural Networks (ANNs) were first formulated by McCulloch and Pitts in 1943(Graupe, 2007). According to Chan et al. (1995), Neural Network have not only the competence to learn a complex nonlinear dataset from massive body of given attributes, but can tolerate to fault and noisy condition in resemblance to human brain as well.

One of the outstanding examples of neural networks is Radial Basis Function (RBF). According to Gan et al. (2012), RBF neural Network which was originally conceived by Broomhead and Lowe in 1988 has characterized with fast training speed, strong learning capability and simple topological architecture. Idri et al. (2010) and Gan et al. (2011) described that it consists of only three different layers e.g. the input layer which accepts source dataset; the hidden layer that uses radial basis function to compute its output, and the output layer which represents the result of the network. According to Kurban and Beşdok (2009) an Fernández-Navarro et al. (2011), the activation function which is implemented is usually the Gaussian function, although in some situations (e.g. time series) other functional forms including thin-plate spline functions, multi-quadratic functions and sigmoidal functions are applied.

All neural networks are classified into two main categories of training algorithm, namely: supervised neural network and unsupervised neural network. Bors (2001) proved that RBF usually subclasses under supervised category. The supervised category works with sample of datasets labeled with the training dataset.

This dataset is presented to the inputs at the beginning of the learning process to determine the correct outputs. As in Kattan et al. (2010) an output value that is close to the desired output could be achieved through an iterative continuous process and adjustment of the network weights. Although back-propagation algorithms became one of the most popular methods used to train ANNs, however , it has two drawbacks: firstly differentiable transfer function is required and secondly possibility of trapping into the local minima is too high. Many Stochastic Global Optimization (SGO) techniques such as evolutionary algorithms are adopted for the training of ANNs in order to overcome the local minimum problems.

Harmony Search Algorithm (HSA), a powerful music-based meta-heuristic SGO algorithm, not inspired by biological and physical processes is also adopted for the training of ANNs (Kulluk *et al.*, 2012) and (Kattan and Abdullah, 2011). HSA performed better than the standard BP algorithm as reported in (Kattan *et al.*, 2010). The following section depicts the background of this study.

1.2 Problem Background

The emergence of radial bases function as an alternative of ANN was first perceived late 80's, although their related counterpart – pattern recognition technique – existed long ago (Bors, 2001). RBF Neural Network was originally perceived and added to the ANN by Broomhead and Lowe (1988), who were inspired by the local response observation in the biologic neurons. RBF Networks have been implemented in a wide area of engineering and science fields, because of their advantages over other well known networks such as: their optimized ability, simple topological architecture, accuracy in dynamically nonlinear approximation and fast and easy learning algorithms (Gan *et al.*, 2012).

Bors (2001) mentioned in his paper that radial basis functions are entrenched in two feed-forward neural network layers. In addition to this two visible layers, i.e. the input layer and the output layer, there is a third hidden layer embedded in between them for processing units called *hidden units,* in which RBF which is generally a Gaussian function, is applied to each of them. Qasem and Shamsuddin (2011) proved that the output layer of RBF has the characteristics of linear decision boundary, where as the hidden units of this network are indeed a composition of non-linear mapping.

According to Kurban *et al.* (2009), in various literatures, different algorithms were proposed for training the RBF Network. It is necessary to find appropriate training algorithms for the RBF Neural Network.

One of the most popular training algorithms in the domain of RBF Neural Networks is the back-propagation technique, which is a gradient-descent method to minimize the mean squared error between the desired outputs and the actual outputs for the particular inputs to the networks. However, as in Kulluk et al. (2012), BP has some drawbacks: the first is that it require a differentiable neuron transfer function and the second is the high possibility to converging into local minima.

To deal with this convergence problems, some researchers proposed two derivative based algorithms for training RBF networks, such as the gradient descent (GD) algorithm and Kalman filtering (KF). Kurban and Beşdok (2009) and Tuba *et al.* (2009) proved that both algorithms need a prolonged time and have convergence weaknesses to the local minima and procedure of discovering the optimal gradient. In order to overcome this drawbacks, several global optimization methods could be applied for training RBF networks in accordance with the various science and engineering problems. Some of these algorithms are: genetic algorithms (GA), the particle swarm optimization (PSO) algorithm, the artificial immune system (AIS) algorithm and the differential evolution (DE) algorithm.

These meta-heuristic SGO techniques are inspired by biological processes which has the characteristics of training algorithms that overcome the aforementioned inefficiencies. Besides that, Harmony Search (HS) algorithms are young meta-heuristic SGO methods which resemble the other SGO meta-heuristic techniques except that they are inspired by music improvisation. Although HS have been reported that they performed better than BP in adopting Feed Forward Neural Networks (FFNN) as in (Kattan *et al.,* 2010), they were not applied to RBFNNs so far. The following section will illustrate more on meta-heuristic algorithm.

1.2.1 Meta-Heuristic Algorithms

In order to deal with the local minimum problem, many global optimization techniques have been adopted for the training of RBF Neural Networks in this case. Heuristic algorithms typically intend to find a good solution to an optimization problem by 'trial-and-error' in a reasonable amount of computing time. Here 'heuristic' means to 'find' or 'search' by trials and errors. Generally, local search methods are heuristic methods because their parameter search is focused on the local variations, and the optimal or best solution can be well outside this local region. However, a high-quality feasible solution in the local region of interest is usually accepted as a good solution in many optimization problems in practice if time is the major constraint.

Meta-heuristic algorithms are higher-level heuristic algorithms. The word '*meta*-' stands for 'higher-level' or 'beyond', so a literal meaning of meta-heuristic is to find the solution through high level techniques, although certain trial-and-error processes are still used. Broadly speaking, meta-heuristics are considered as higher-level techniques or strategies which intend to combine lower-level techniques and tactics for exploration and exploitation of the huge space for parameter search (Yang, 2009). Yang (2009) says that the word 'meta-heuristic' refers to modern high level algorithms including Simulated Annealing (SA), Particle Swam Optimization (PSO), Evolutionary Algorithms such as Genetic Algorithm (GA), and, certainly Harmony Search Algorithm (HSA).

However, Ren *et al.* (2010) mentioned that, the Genetic Algorithm usually spends a long time to find a solution. At the same time there may be premature and slow convergence problems in GA. On the other hand, according to Dian et al. (2011), PSO easily suffers from the partial optimism, which is related to the regulation of its speed and direction. Moreover Grosan and Abraham (2011) summarized the pitfalls of PSO in their book of "Intelligent Systems: A Modern Approach", as follows:

- Particles tend to cluster, i.e., converge too fast and get stuck at local optimum
- Movement of particle carried it into infeasible region
- Inappropriate mapping of particle space into solution space

These drawbacks motivated the proposal of HS which is a new meta-heuristic algorithm to solve those aforesaid problems. A brief discussion about this algorithm will come next.

1.2.2 Harmony Search Algorithm

According to Kulluk *et al.* (2012) Harmony Search Algorithm (HSA) is a meta-heuristic optimization algorithm motivated from the process of making music. In HS algorithm each decision variable (musical instrument) generates a value (note) in order to find the global optimum solution (best harmony). The method uses a stochastic random search based on harmony memory consideration rate and pitch adjustment rate instead of a gradient search. Nowadays HS algorithm has been applied to many diverse optimization problems such as music composition, Sudoku puzzle, timetabling, tour planning, logistics, web page clustering, text summarization, Internet routing, robotics, power system design, structural design, vehicle routing, heat exchanger design and so on.

As far to our knowledge, no study has been done for optimization of RBF Neural Network with HSA. This attracted our attention in training RBF with HSA to improve the performance of the network.

1.3 Problem Statement

According to kulluk *et al.* (2011); Kattan *et al.* (2010) and Hamed *et al.* (2012) training RBF with BP faced some problems such as poor convergence and trapping at the local minima. Genetic algorithm performed robust training without suffering from local minimum problem. However its output production is time consuming and computation expensive (Xie et al., 2011) and (Hamadneh et al., 2012).

Particle swarm optimization attracted the attention of many researchers after several experiments proved its better performance over GA. Although the experiments conducted by many researches showed a plausible achievement, Rini *et al.* (2011) mentioned that PSO easily suffers from the partial optimism, which is related to the regulation of its speed and direction. Moreover Grosan and Abraham (2011) summarized the pitfalls of PSO in their book of "Intelligent Systems: A Modern Approach", with the following three problems: firstly, particles tend to cluster, i.e., converge too fast and get stuck at local optimum. Secondly, movement of particle carried it into infeasible region and finally, inappropriate mapping of particle space into solution space.

Kulluk *et al.* (2011) proved that HS which is a new SGO meta-heuristic algorithm is a good candidate and the most promising variant for training feed forward type NNs. More over Soltani et al. (2011) confirmed that HS is not only faster than PSO but has a significant convergence rate to reach the optimal solution.

So far no study related to the optimization of RBF Neural Network with HSA has been done, therefore two questions that can be perceived from this research are stated as below:

1. Since harmony search proved better performance compared to other optimizing algorithms, can HS algorithm improve the learning capability of RBF network?
2. How much significance can HSA provide in optimizing the RBF neural network?

1.4 The Study Aim

In this study HSA will be employed to investigate the higher convergence rate and the classification performance of RBF neural network's learning capability compared with PSO based RBF neural network

1.5 Dissertation Objectives

The objectives of the study are as follows:

i. To identify existing literature of Radial Basis Function (RBF) and Particle Swarm Optimization (PSO) algorithms and their interaction.
ii. To enhance the training process of RBF neural network by integrating with the Harmony Search Algorithm (HSA).
iii. To compare the results between HSA-RBFN and PSO-RBFN in terms of convergence rate and classification result.

1.6 Dissertation Scope

This study will be confined in the following points in order to fulfill the aforementioned goals.

i. Four datasets which are XOR, Iris, Cancer and Heart disease classification from UCI machine learning dataset have been used for training and testing.
ii. The performance of HSA learning algorithm for RBF Network are compared to PSO algorithm only.
iii. While enhancing RBF Network learning by integrating HSA error function are minimization.

1.7 Dissertation Significance

According to the process of work, there will analysis and continuous experiments that will be targeted to the goals in order to improve the learning capabilities of RBF and make it cost effective by integrating with it this superior HSA which previous researches approved that it has great practical significance in searching for optimal value of large-scale projects problems (Ren and Kezunovic, 2010)(Ren *et al.*, 2010).

Performance metrics: In order to analyze and compare the training capability of the HSA algorithm, four performance metrics will be taken into consideration. These are: overall training time, sum of squared errors, training accuracy and testing accuracy. Accuracy measures the ability of the classifier to produce accurate results.

1.8 The Organization of the Dissertation

This dissertation consists of five chapters. Chapter 1 presents the introduction of the dissertation, problems background, the problem statement, objectives, scope and significance of the study. In Chapter 2, the literature reviews on ANN, BP, RBF, PSO and HSA is discussed. Chapter 3 illustrates research methodology. Chapter 4 displays the experimental results, finally the conclusion and suggestions for future work are explained in Chapter 5.

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