RADIAL BASIS FUNCTION NEURAL NETWORK LEARNING
WITH MODIFIED BACKPROPAGATION ALGORITHM

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This dissertation is dedicated to my family for their endless support and encouragement.

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ABSTRACT

Radial Basis Function Neural Network (RBFNN) is a class of Artificial Neural Network (ANN) widely used in science and engineering for classification problems with Backpropagation (BP) algorithm. However, major disadvantages of BP are due to the relatively slow convergence rate and always being trapped at the local minima. To overcome this problem, an improved Backpropagation (MBP) algorithm using modified cost function was developed to enhance RBFNN learning with discretized data to enhance the performance of classification accuracy and error rate convergence of the network. In RBFNN learning with Standard Backpropagation (SBP), there are many elements to be considered such as the number of input nodes, number of hidden nodes, number of output nodes, learning rate, bias rate, minimum error and activation functions. These parameters affect the speed of RBFNN learning. In this study, the proposed MBP algorithm was applied to RBFNN to enhance the learning process in terms of classification accuracy and error rate convergence. The performance measurement was conducted by comparing the results of MBP-RBFNN with SBP-RBFNN using five continuous and five discretized dataset with ROSETTA tool kit. Two programs have been developed: MBP-RBFNN and SBP-RBFN. The results show that MBP-RBFNN gave the better results in terms of classification accuracy and error rate compared to SBP-RBFNN, together with statistical test to verify the significance of the results on the classification accuracy.

ABSTRAK

Rangkaian Saraf Fungsi Asas Radial (RBFNN) merupakan satu kelas rangkaian saraf buatan (ANN) telah banyak digunakan dalam bidang sains dan kejuruteraan berkaitan masalah pengelasan dengan algoritma rambatan balik (BP). Walau bagaimanapun, kelemahan utama BP adalah terhadap kadar penumpuan yang agak perlahan dan sering terperangkap dalam minimum setempat. Untuk mengatasi masalah ini, algoritma penambahbaikan rambatan balik (MBP) menggunakan fungsi kos yang diubahsuai telah dibangunkan untuk meningkatkan pembelajaran RBFNN dengan data terdiskret bagi meningkatkan prestasi ketepatan pengelasan dan penumpuan kadar ralat rangkaian. Dalam pembelajaran RBFNN menggunakan rambatan balik piawai (SBP), terdapat banyak elemen yang perlu dipertimbangkan seperti bilangan input nod, bilangan nod tersembunyi dan nod output, kadar pembelajaran, kadar *bias*, ralat minimum dan fungsi pengaktifan. Parameter ini memberi impak kepada kepantasan pembelajaran RBFNN. Dalam kajian ini, algoritma MBP yang dicadangkan terhadap RBFNN dilaksanakan bagi meningkatkan proses pembelajaran dari segi ketepatan pengelasan dan kadar penumpuan ralat. Pengukuran prestasi dibuat dengan membandingkan keputusan MBP-RBFNN dengan SBP-RBFNN menggunakan lima set data selanjar dan lima set data terdiskret dengan alatan ROSETTA. Dua aturcara telah dibangunkan: MBP-RBFNN dan SBP-RBFN. Hasil kajian menunjukkan bahawa MBP-RBFNN memberikan keputusan yang lebih baik dari segi ketepatan pengelasan dan kadar ralat berbanding dengan SBP-RBFNN bersama-sama dengan ujian statistitk bagi mengesahkan kesahihan keputusan terhadap ketepatan pengelasan.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BMI	Body Mass Index
BP	Backpropagation
BP-RBFN	Backpropagation Radial Basis Function Network
DBMS	Database Management System
DNA	Deoxyribonucleic acid
FPG	Fasting Plasma Glucose
GA	Genetic Algorithm
GAP-RBFN	Growing and Pruning Radial Basis Function Network
GUI	Graphical User Interface
HDL	High Density Lipids
HRL	Hand Rock Laboratory
HRPSO	Hybrid Recursive Particle Swarm Optimization
LDL	Low Density Lipids
LMS	Least Mean Squares
MBP	Modified Backpropagation
MBP-RBFN	Modified Backpropagation Radial Basis Function Network
MIMO	Multi-Input, Multi-Output
MSE	Mean Squared Error
NFCM	Normalized Fuzzy C-Mean
ODBC	Open Database Connectivity
OPA	Optimal Partition Algorithm
PSO	Particle Swarm Optimization
RBFN	Radial Basis Function Network
QPSO	Quantum-Behaved Particle Swarm Optimization
RBF	Radial Basis Function

RBFN	Radial Basis Function Network
RBFNN	Radial Basis Function Neural Network
RLS	Recursive Least Squares
ROLS	Recursive Orthogonal Least Squares
ROSETTA	Rough Set Toolkit for Data Analysis
SBP	Standard Backpropagation
SBP-RBFN	Standard Backpropagation Radial Basis Function Network
SI	Swarm Intelligence
SOM	Self-Organizing Map
SVD	Singular Value Decomposition
TC	Total Cholesterol Level
XML	Extensible Markup Language

LIST OF SYMBOLS

η	learning rate
α	momentum rate
φ	activation function
θ	the bias
O_i	Output of input layer *(i)*
O_j	output of hidden layer *(j)*
O_k	output of output layer *(k)*
(t)	time in seconds
W_{ij}	weight connecting layers *(i) to (j)*
W_{jk}	weight connecting layers *(j) to (k)*
w_{kj}	weight connecting layers *(k)* to *(j)*
W_{ji}	weight connecting *(j)* and *(i)*
$\Delta w_{kj}(t)$	change in weight from *(k)* to *(j)* at time *(t)*
$\Delta w_{kj}(t)$	change in weight from *(k)* to *(j)* at time *(t)*
θ_j	bias of hidden layer *(j)*
θ_k	the bias of *(k)*
δ_k	error of at node *(k)*
t_k	target output of *(k)*
net	weighted sum
Wi	weight of input layer *(i)*
Xi	input neuron *(i)*
$w_{ji}(t)$	weight from *(j) to (i)* at time *(t)*
$\Delta w_{ji}(t)$	change in weight from hidden layer *(j)* to input layer *(i)* at time *(t)*
X'	new normalized value
$c_{ji}(t)$	centre from *(j)* to *(i)* at time *(t)*

Δc_{ji}	change in the centre
σ_j	width of *(j)*
$\Delta \sigma_j$	change in width of *(j)*
x_{ji}	input from *(j)* to *(i)*

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CHAPTER 1

INTRODUCTION

1.1 Overview

Artificial Neural Network (ANN) was developed as a parallel distributed system that is inspired by the biological learning process of the human brain. The primary importance of ANN is its capacity of learning to solve problems through training. There are many types of ANN and among them is Self-Organizing Map (SOM), Backpropagation Neural Network (BPNN), Spiking Neural Network (SNN), Radial Basis Function Neural Network (RBFNN), etc. RBF was first proposed in 1985 and subsequently Lowe and Broomhead (1988), were the first to apply RBF to design neural network. In their design, they compared RBFNN with the multilayer neural network, and they showed the relationship that exists between them. However, Moody and Darken (1989), proposed a new class of neural network, the RBFNN.

The RBFNN is a type of ANN which uses RBFs as activation functions. It is an ANN that is unique in its own right. This is because RBFNN has only three layers. It has only one hidden layer unlike other types of ANN that have one or more hidden layers. It is also a network that is feed forward and fully connected (Chen, 2010). The RBFNN output is an arrangement of RBFs of inputs and neuron parameters linearly. RBFNN has several benefits above its predecessors. Some of the benefits include having simple network architecture, ability to approximate better and also algorithms that learn faster (Chang, 2013). RBFNNs are used to solve problems such as classification problems, function approximation, system control, and time series prediction.

As a result of the above mentioned benefits, RBFNN enjoys patronage in science and engineering. According to Yu *et al.* (1997) RBFNN has only three layers. Radial function is applied as activation function for all the neurons of the hidden layer. Also, output layer neuron on the other hand, computes a weighted sum. RBFNN training is normally divided into two stages. RBFNN training is in two stages. Between input neurons to hidden neurons is the first stage where clustering takes place using unsupervised learning and nonlinear transformation while on the other hand at the second stage, supervised learning is implemented between the hidden nodes and the output nodes with linear transformation taking place. Clustering algorithms are used to determine the centre and weight of the hidden layer. Least Mean Squares (LMS) algorithm applied between hidden and output layer to determine the weights (Yu *et al.*, 1997). Other clustering algorithms can also be used such as, decision trees, vector quantization, and self-organizing feature maps.

RBFNN's hidden node performs distance transformation of the input space. The RBF fundamental design maps non-linear problem into a high dimension space which turns the problem into a linear one. Linear and non-linear mapping is implemented from input to hidden layer and hidden to output layer of RBFNN respectively. The weights thou can be adjusted have a value of 1 between the input layers and the hidden layers (Chen, 2010). The hidden layer nodes determine the behaviour and structure of the network. Gaussian function is used to activate the hidden layer (Qasem and Shamsuddin, 2009).

Functions given by hidden neurons create random starting point for input patterns (Qu *et al.*, 2003). In this context the training is a means of adjusting the values of the weights and biases of the neurons continuously until a predetermined condition is satisfied i.e. defined error function. There are many ways to minimize the error functions by fine-tuning the weights such as using BP algorithms. BP algorithm has been widely used as training algorithm for ANN (Zweiri *et al.*, 2002), this also applies to RBFNN.

BP algorithm is employed to train ANN in supervised learning mode. Supervised learning is guided by the desired target values for the network. During the training, the aims are to match the network results to the expected target values. Genetic Algorithm (GA) is a famous evolutionary technique also used for training ANN (Mohammed, 2008). In RBFNN training, we need to first determine the cluster centres of the hidden nodes, by using clustering algorithms.

Clustering algorithms are capable of finding cluster centres that best represents the distribution of data. This algorithm has been used for RBFNNs training. K-means algorithms have also been used to train RBFNN with some limitations in real applications. Several other algorithms have been used in clustering such as Manhattan distance, Euclidean distance, DBSCAN algorithm, etc. Particle Swarm Optimization (PSO) (Cui *et al.*, 2005) is another computational intelligence method that has been widely used in data clustering.

Research has been going on for years on how to improve BP learning algorithm for better classification accuracy. In this study, we are applying the Modified backpropagation (MBP) with Modified Cost Function (MM) by (Shamsuddin *et al.*, 2001) with improved learning parameter value to train RBFNN with discretized data. Thus, this study attempts to investigate the performance of RBFNN by determining values for convergence or learning rate and correct classification accuracy of the network. In this study, five standard dataset will be used as yardstick for classification problems to illustrate the efficiency improvement of the proposed algorithm. This study will compare the result of proposed algorithm (MBP-RBFNN) with the result of the original Standard Backpropagation Radial Basis Function Neural Network (SBP-RBFNN). We would use the MBP by (Shamsuddin *et al.*, 2001) error function to test the classification accuracy and convergence for classification problems with discretized data.

Discretization is a method of dividing range of continuous attributes into disjoint regions or intervals. It is one way of reducing data or changing original continuous attribute into discrete attribute as a form of data preprocessing stage (Goharian *et al.*, 2004). The advantages of discretization are reduction in data size and simplification, easier to understand and easy to interpret, faster and accurate training computation process, and the representation is non-linear (Dougherty *et al.*, 1995; Leng and Shamsuddin, 2010; Liu *et al.*, 2002). Based on different theoretical origins there are many types, such as supervised versus unsupervised, global versus local and dynamic versus static (Agre and Peev, 2002; Saad *et al.*, 2002).

1.2 Problem Background

RBFNN is an ANN, which uses RBF as activation functions. RBFNN forms a unique kind of ANN architecture with only three layers. In RBFNN, different layers of the network perform different tasks. This kind of behaviour is the resultant of the primary issue or problem with RBFNN. Therefore, a good practise here is separating the procedure or activities that took place in the hidden and output network layer by using various techniques.

In addition, to train RBFNN, we can take a two-step training strategies. The first step is called unsupervised learning. Unsupervised learning is used to determine RBFNN centres and widths of the clusters with clustering algorithms. This procedure is known as Structure Identification Stage. The second step is called supervised learning. This is employed to determine the weights from hidden to output layers, otherwise known as parameters estimation phase which has high running time.

Moreover, other weakness is that local information is used in determining the centres of hidden units. It is useful to merge the structure identification with parameters estimation as one process. On the other hand, this problem cannot be easily solved by the standard techniques. Therefore, this study proposed RBFNN training with MBP algorithm using discretized data. With the hope that this proposed method will give better classification accuracy and lower error convergence rates.

1.3 Problem Statement

Several parameters in RBFNN trained with SBP (otherwise known as SBP-RBFNN) need to be considered. The activation function, number of nodes in all the three layers, the learning and momentum rates, bias, and minimum error. All these factors will have an effect on the convergence rate of RBF Network training. In this study, the proposed method will use MBP algorithm to train RBFNN to give the optimum pattern of weight for better classification of data. Our focus is limited to the correct classification accuracy and error rate convergence.

The entire problem involves minimization of the error function. This is somewhat complex using the traditional learning methods, primarily due to the existence of the number of units in the hidden layer. MBP algorithm can be applied to obtain the best convergence rate and the classification accuracy of RBFNN training. Therefore, this study will investigate the performance of the MBP-based learning algorithm for RBFNN in terms classification accuracy and error convergence rates.

The research questions of this study can be said as:

1. Could MBP algorithm enhance learning capability of RBFNN with discretized data?
2. How significant is MBP in training the RBFNN with discretized data?
3. How efficient is the MBP cost function in enhancing the performance of RBFNN with discretized data?

1.4 Aim

This study aims to examine the effectiveness of Modified BP algorithm, with modified cost function in training RBF Network using discretized datasets as opposed to RBFNN Network trained with standard Backpropagation algorithm with respect to error convergence rate, correct classification accuracy and cost function.

1.5 Objectives

The objectives of this study are:

1. To develop a MBP algorithm for RBFNN learning method.
2. To compare the performance of the proposed MBP-RBFNN method with SBP-RBFNN in terms of classification accuracy and error rate.
3. To investigate the effectiveness of discretized dataset on MBP-RBFNN algorithm on continuous dataset.

1.6 Scope

To achieve the stated objectives above, the scope of this study is limited to the following:

1. Five standard datasets: XOR, balloon, Iris Cancer and Ionosphere, will be used in this study.
2. To apply ROSETTA Toolkit for dataset discretization.
3. Modified BP-RBF Network with discretized data.
4. The performance of MBP training algorithm for RBFNN will be compared to RBFNN Network trained with SBP algorithm.

5. The network architecture consists of three layers: input, hidden and output to standardize the comparison criteria.
6. The coding of the MBP-RBFNN and SBP-RBFNN programs will be in C Language using Microsoft Visual C++ 2010, running on Microsoft Windows 7 Professional on a HP-Compaq-8100 Elite SFF PC running on Intel(R) Core(TM) i5 CPU with 2.00 GB of internal memory and 32-bit OS Machine.
7. SPSS version 16.0 was used to carry out t-test statistical analysis only on the classification accuracy in k-fold experiments to ascertain the correlation of the results obtained from the two algorithms.

1.7 Importance of the Study

The performance of RBFNN with Modified BP algorithm, standard BP algorithm Network and other methods in literature will be analysed. Hence the best method can be ascertained for RBFNN training. It would be significant in confirming that Modified BP can be successfully be used to solve challenging problems.

1.8 Organization of the Thesis

The study comprise of five chapters starting from chapter one to chapter five: Chapter 1 provides a general introduction to the study. It comprises sections such as overview, problem background, problem statement, aim, objectives, scope and importance of the study. Chapter 2 deals with the literature review on previous studies related to this study, it discusses ANN, BP algorithm, classification problem Cost function, RBFNN, data clustering, least means squares (LMS) algorithms, discretization, rough set for data analysis and summary. Chapter 3 covers the methodology of the research, which focuses on the application of the Modified BP algorithm to enhance RBFNN Network training, dataset used in the experiments and how they are used. Chapter 4 presents and discusses the experiments and experimental setup as well as the analysis of the experimental results. Chapter 5 contains conclusions and suggestions for future work.

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