Chapter 1

Introduction

1.1 Literatures Review

In 1991, John Platt proposed the resource-allocating network (RAN), one kind of radial basis function (RBF) neural network [1], [2], for the problem of function interpolation. His network has two layers consisting of one hidden layer and one output layer. Each hidden neuron uses a Gaussian distribution function as its activation function. The training season starts with a blank node in the hidden layer. At the beginning, the first hidden neuron is placed at the location of the first training input. Platt used Least Mean Square (LMS) gradient descent rule and Extended Kalman Filtering (EKF) parameters for variable adjusting which are height, centers and widths of the nearest hidden nodes [3], [4].

In 1999, Q. Zhu, Y. Cai and L. Liu proposed a general strategy of the learning process by starting with a near-minimal network and adding nodes until the network has the desired size or is "good enough" for the task at hand. The growth process uses the local statistical quantities to guide the insertion and deletion of hidden nodes with multivariate Gaussian function [5].

The statistical characteristic is not only useful for the learning, but also useful for the pruning of the redundant hidden node (for decreasing the number of hidden nodes). In 1993, Russell Reed and his student member discussed about the pruning algorithm [6].

Various neural network-pruning techniques have been developed in the aim to find the neural networks of suitable sizes for a give certain problem. The multitude of techniques and the ongoing research can be explained by the difficulties to find a minimal neural network for a specific application. The pruning can be performed on either the connections between neurons or the neuron itself. For the connection pruning, the most famous among these methods are the smallest weight removal, the smallest variance, and the optimal brain damage method [1].

More recent approaches are also aimed at the estimation of the best moment for removing nodes and how many nodes to be pruned, as well as to optimize the performance of the resulting network, as well as its size, and the training time. Hence, a setting of any variable in the network was found to be good for one data set might be unsuitable for another. In the same way, the training parameters are subject to changes when they are applied to new neural network architectures. A logical way to a adapt such a method to new network architecture is to perform the experiments with the original neural network architecture to find the suitable parameter settings and to gain experience with these methods.

Statistical analysis of Bootstrap Method for estimating the statistical characteristics of the training data is a computer-intensive method widely used in signal processing applications [8]. The idea of Bootstrap is to estimate the variability of a statistical variable across the samples by looking at each observation of the variable across the generated samples set [7], [9]. This method is suitable for achieving generalization of a neural network whose the all-actual training data are not available. The generalization is a way of preparing network for a new incoming data set, which may occur while the trained network is used. A new incoming data set is a set of data vector that is in the same class as the training data class but they will be experimented later near the training data in the future. Then, in some part of the generalization, the statistical method is used to be a way of preparing network for that data set by looking at the population characteristic of the data [1], [10].

1.2 Problem Identification

This thesis presents a method for evaluating a generalization of the classification problem in a Radial Basis Function Neural Network (RBF NN). In the generalization, the goal is to correctly classify all the incoming untrained data vectors. On the traditional RBF NN, an algorithm performed a Multivariate Gaussian function as the activation function of the hidden nodes. The learning algorithm needs the calculation of the inversion of the covariance matrix in every step of the learning [5]. Thus, the way to reduce this cost is by the replacement of a traditional multivariate Gaussian function with a new elliptic radial basis function. The generalization of this new kind of RBF is also considered.

1.3 Objectives of The Research

The objectives are (1) to develop a new elliptic radial basis function to increase the learning generalization and (2) to apply Bootstrap Method to estimate the size of the elliptic radial basis function so that it can cover most of the new incoming data, which do not exist in the training and testing sets.

1.4 Scope of The Research

This research present an enhancing RBF Neural Network in the way of following conditions.

(1) Only classification problem is considered.

(2) The data in each problem are in a 2-dimentional space.

(3) In the training, weights are adjusted by the gradient descent algorithm.