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PSO Based SVM as an Optimal Classifier for Classification of Radar Returns from Ionosphere

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ABSTRACT : The aim of this paper is two fold. First, we present a through experimental study the different Artificial Neural Networks classifier for classification of radar returns from Ionosphere dataset. Second, we propose a novel classification system based on particle swarm optimization (PSO) to improve the generalization performance of the SVM classifier. For this purpose, we have optimized the kernel parameters of SVM classifier. The experiments were conducted on Jonhs Hopkins Ionosphere database. The comparison of different Neural Networks classifier and PSO-SVM is done based on Ionosphere dataset from UCI machine learning repository. The results show that RBFNN typically provide better classification results. When comparing to techniques applied to binary classification problems. Also SVM Classifier with RBF kernel gives best classification accuracy on training set. And PSO-SVM classifier with optimized kernel parameter selection for classification of radar returns from ionosphere dataset gives better accuracy and improves the generalization performance.

Keywords: Artificial Neural Network, BPNN, RBFNN, SVM, Particle swarm Optimization (PSO).

I. INTRODUCTION

Classification is one of the important decision making tasks for many real world problems. Classification will be used when an object needs to be classified into a predefined class or group based on attributes of that object .Radar target identification is a domain very rarely explored by Artificial neural networks (ANN), where the need for intelligent knowledge extraction is important. Therefore, a decision of optimal classifier for classification of radar returns from the ionosphere has been investigated in this papers using ANN & SVM. The radar data is obtained from Johns Hopkins University Ionosphere database [1] collected by a system in Goose Bay Labrador, which consists of a phased array of 16 high frequency antenna with a total transmitted power on the order of 6.4 KW. The targets were free electrons in the ionosphere. 'Good' radar returns are those showing the evidence of some type of structure in the ionosphere.' Bad' returns are those that do not their signals pass through the ionosphere. Received signals were processed using an auto correlation function whose arguments are the time of a pulse and the pulse number. There were 17 pulse number for the Goose Bay system. Instances in this database are described by two attributes per pulse number, corresponding to the complex values returned by the function resulting from the complex electronic signal. Thus, there are 34 continues valued attributes with respect to inputs and one additional attributes denoting class that is either 'good' or 'bad'(binary classification task). There are total 351 instances in this database.

To solve the classification problems, many classification techniques have been proposed some of the successful techniques are Artificial Neural Networks(ANN), Support vector machine (SVM). Optimal design of classifier is investigated using multilayer perceptron neural network (MLPNN) trained with error back propagation algorithm on this database [2]. Using the first 200 instances for training which were carefully split almost 50% positive & 50% negative (equiprobable), MLPNN trained with EBP attained an average of about 96% accuracy on the remaining 151 test instances. Accuracy on good instances was bad instances was much higher than for bad instances.

Other researcher's attempts modular ANNs for efficient radar target classification [3]. Radial basis function neural networks are used to classify real life audio radar signals [4].

This papers is organized as follows, in section II & III gives proposed methodology with three configurations namely, BPNN, RBFNN, PSO-SVM are examined in this paper for designing simple optimal classifier and compare performance with respect to the performance measure such as MSE and percentage classification accuracy on training and testing set. Finally, the conclusion is discussed in section VI.

II. MATERIALS AND METHODS

The radar dataset having 351 samples with 34 attributes and one target value. For classification database are partitions into 200 samples for training set and 151 samples for testing set to generalize the design network. The dataset is available on UCI Machine learning repository. The Proposed classifications methods are discuss in following sections.

III. CLASSIFICATION METHODS

A. BP Neural Network Classifier

It is shown that from the literature review a BPNN having single layer of neurons could classify a set a set of points perfectly if they were linearly separable. BPNN having three layers of weights can generated arbitrary decision regions which may be non convex and disjoint. However arbitrary decision boundaries can not be generated with just two layers of weights. BPNN is based on processing elements, which compute a nonlinear function of the scalar product of the input vector and a weight vector. Its configuration is determined by the number of hidden layers, numbers of the neurons in each of the hidden layers as well as the type of the activation function used for the neurons. Train Levenberg Marquart algorithm is used for determined the connection weights from the samples. The BPNN structure is evaluated on training set and test set. The test data are then used to accesses how well the network has generalized. Fig. 2 shows structure of BPNN classifier.

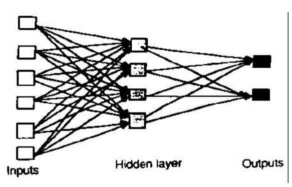

Fig. 2. BPNN as Classifier.

B. RBF Neural Network

A radial basis function (RBF) is a real valued function whose value depends only on the distance from the origin, so that $\Phi(x) = \Phi(||x||)$; or alternatively on the distance from some other point *C*, called a center.RBF NN is a nearest neighbor classifier. It uses Gaussian transfer function having radial symmetry. The centers coefficient vector $W = [W1, W2, W3, \ldots, Wn]$, $f(x)$ being a real valued vector $x = [x1, x2, x3, ..xn]$ implements the input-output map of the RBFNN. Any arbitrary continuous function can be approximated with an RBFNN if localized Gaussian are placed to cover the space, the width of each Gaussian is controlled the amplitude of each Gaussian is set. Figure 3 shows RBF NN architecture.

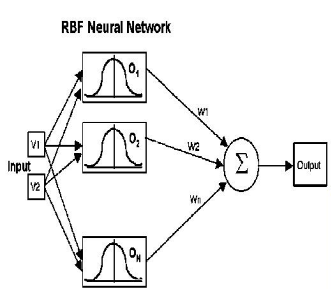

Fig. 3. RBFNN as classifier.

C. SVM Classifier

SVM is a new paradigm of learning system. The techniques of SVM, developed by Vapnik was proposed initially for classification problems of two classes. SVM use geometrical properties to exactly calculate the optimal separating hyper plane directly from the training data. They also introduce methods to deal with non linearly separable cases, *i.e.* where no separating straight line can be found as well as with cases in which there is noise and /or outliers in the training data, *i.e.* some of the training samples may be wrong.

Basically, the SVM is a linear machine working in the highly dimensional features space formed by the nonlinear mapping of the n-dimensional input vector x into a K-dimensional features space ($k > n$) through the use of a mapping $\Phi(x)$. The following relation gives the equation of hyper plane separating two different classes. $Y(x) = W^T \Phi(x)$, where w is the weight vector of the network. Fullfillment of condition $Y(x) > 0$ means one class and $Y(x) < 0$ means the opposite one.

The most distinctive fact about SVM is that the learning task is reduced to quadratic programming by introducing the so called Lagrange multipliers. All operation in learning and testing modes are done in SVM using kernel functions. The kernel is defined as $k(x, xi) = \Phi^T(xi)\, \Phi(x)$. The best known kernels are linear , polynomial, radial basis functions and sigmoid functions. The problem of learning SVM, formulated as the task of separating learning vectors x, into two classes of the destination values either $di = 1$ or $di = -1$ with maximal separation margin is reduced to the dual maximization problems of the objective function. '*c*' is the regularizing parameter and determines the balance between the maximization of the margin and minimization of the classification error .The solution with respect to Lagrange multiplier gives the optimal weight vector.

In the present study, RBF function is used as kernel and the kernel parameters γ and c, which provide the best classification, are fixed experiment before learning. The learning of support vector referred to as the separation of learning vector xi in two classes of designation values either $di = 1$ or $di = -1$ with maximal separation margin.

Fig. 4 shows the conceptual SVM algorithm for classification.

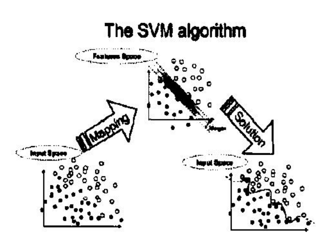

Fig. 4. SVM as Classifier.

IV. PSO ALGORITHM

Particle swarm optimization is a kind of evolution computation, which is an iterative optimization instrument similar to genetic algorithm PSO analogy prey behavior of birds. Such a scenario: a group of bird search food at random. In this area, there is only one food, however all birds don't know where the food is ,but know the distance to the food. Then what is optimal strategy to find food? Currently the simplest and most effective method is to search the food from this model to solve this kind problem. Each optimization is to search a bird in space which is called as 'particle'. All particles have fitness value determined by optimization function, every particle also have one velocity to determine direction and distance. Then particles follow the optimization particle to search PSO as are one random particle (random solution) iterative method is particles update themselves by tracking two "extreme" particles. The first is the optimization solution found by particles. This kind of solution is called as Pbest, the other is the optimization found by species. This kind of extremum is called as global extremum. When the two optimization are found, particle updates themselves by equation1 and 2 to find their own velocity and location.

$$v = v + c1 * \text{rand}() * (\text{pbest-present}) + c2 * \text{rand}() * (\text{gbest-present}) \quad \text{... (1)}$$

$$\text{Present} = \text{present} + v \quad \text{... (2)}$$

where v is the particles velocity, present is the particles position currently rand() is random number among (0, 1). $c1$, $c2$ as learning factor. Commonly $c1 = c2 = 2$. The velocity in any dimension is limited in maximum velocity exceeds v_{max}, and then the velocity is v_{max}.

V. RESULTS

In this section, experimental results regarding the evaluation process of the developed classifiers are presented. In order to compare the performance of neural network techniques. Firstly dataset is splits into 80% as training set and 20% testing set. In the experiment, MATLAB software is used to design and test each neural networks and SVM. Table I. shows the performance results obtained by BPNN, RBFNN and SVM classifier for same dataset.

VI. CONCLUSION

This paper presents the comparison of three neural network classifier BPNN, RRFNN, and PSO-SVM for binary classification on radar dataset. Each neural network techniques selected for this comparison has different structures and different advantages and disadvantages. While RBFNN and SVM have simpler architectures and they can train data faster than BPNN.

TABLE I. RESULTS

classifier	Parameters	Classification accuracy (%)	
		Training set	Evaluation set
BPNN	Trainlmfunction,MSE	84	81.75
RBFNN	Spread,MSE	100	82.78
SVM-RBF	C=1,gamma=1	100	68.21
PSO-SVM	c1=c2=1.3, np=5, Dim=4,C=1,gamma=3	100	82.78

In terms of performance comparison based on the classification accuracy as shown in Fig. 5. We found that generally the results achieved by RBFNN and PSO-SVM are higher than other techniques with best generalization.

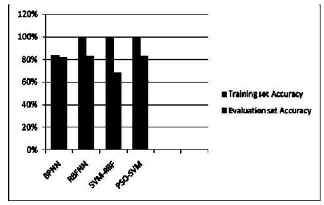

Fig. 5. The comparison of classification Accuracies on Radar dataset.

From results, it can be concluded that RBFNN is suitable for given task. The results of the experiments show that RBFNN can provide good results for both set. Also SVM is good for training set but not maintained performance for test set for generalization. The proposed PSO -SVM Classifier is optimal classifier for classification of radar returns from ionosphere database.

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