Spectrum Sensing using Probabilistic Neural Networks in Cognitive Radio Network

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Abstract

Prediction of potential idle times of different channels based on the past information allows a cognitive radio to select the best channels for control and data transmission. For a successful cognitive radio, learning is one of the most important factors. Cognitive radio with enhanced Artificial Intelligence (AI) techniques leads to design and development of algorithm that enable computer to learn. The learning mechanisms are capable of utilizing measurements sensed from the environment, gathered experience and stored knowledge to improve the radio operation and to guide decisions and actions. This paper presents the learning schemes that are based on artificial neural networks; in particular, Neural Network (NN) and probabilistic neural network (PNN). Based on the intelligent radio learning schemes, an effective training approach is proposed. Simulations demonstrate that the novel technique beats existing hierarchical approaches, and present better performance.

1. Introduction

Intelligence is needed to keep up with the rapid evolution of wireless communications, especially in terms of managing and allocating the scarce, radio spectrum in the highly varying and different modern environments. Cognitive radio systems promise to handle this situation. Cognitive radio [1] is an intelligent wireless communication system that is aware of its environment, can also learn from experience and can make changes to certain operating parameters (e.g. transmit-power, carrier-frequency, and modulation strategy) to adapt to the incoming RF stimuli in real-time. The main objective of a cognitive radio is to have a highly reliable communications with efficient utilization radio spectrum in order to satisfy the user needs [2].

A wireless network designed based on the cognitive radio technology is referred to as a Cognitive Radio Network (CRN). A CRN is composed of two types of users, namely, the primary users (licensed users) and the secondary users (unlicensed users). The primary users have a higher priority than the secondary users in accessing the channels in the licensed spectrum. In most cases, the secondary users in a CRN logically divide the channels allocated to the primary users into slots [3]. Within each slot the secondary user has to sense the primary user activity for a short duration and accordingly accesses the slot when it is sensed idle. The idle slots are also called spectrum holes or white spaces. Thus the secondary users can access the licensed spectrum without causing any harmful interference to the primary users. Once the neural networks are trained, the computational complexity is significantly reduced.

Cognitive radio is a merge of AI techniques and wireless communication [4]. Cognitive radio with enhanced AI techniques is used in a rapidly changing environment. AI field that concerned with the design
and development of algorithm enable the computer to learn. It suits for the situation that based on the past experience, learn by example and learn by analogy [5]. Reasoning and learning techniques is a fundamental constraint on cognitive radio field. The capability to improve is provided by an intelligent software package called a cognitive engine [6]. The cognitive engine derives and enforces decisions to the software-based radio by continuously adjusting its parameters, observing and measuring the outcomes and taking actions to move the radio toward some desired operational state [7].

Cognitive radios are capable of learning lessons and storing them into a knowledge base, from where they may be retrieved, when needed, to assist future decisions and actions. The integration of a learning engine can be important especially for the channel estimation, for improving the stability and reliability of channel and evaluation of the configuration capabilities, without relying solely on the recent measurements. There are many different learning techniques available that can be used by a cognitive radio ranging from pure lookup tables to arbitrary combinations of machine learning techniques that include artificial neural networks, evolutionary/genetic algorithms, reinforcement learning, hidden Markov models, etc. In this paper we proposed two learning schemes NN and PNN, different issues such as learning algorithm, performance, efficiency and learning rate are discussed. The paper is aimed at overcoming the existing drawbacks faced by conventional neural networks and also aimed to having improved sensing of the channel.

Section 2 briefly presents the basic NN algorithm. The main purpose of this section is to introduce notation and concepts which are needed to describe the NN algorithm. The PNN algorithm is then presented in Section 3. In Section 4 the PNN algorithm is compared with the NN algorithm and with a variable learning rate variation of back propagation. Section 5 contains a summary and conclusions.

2. NEURAL NETWORK (NN) ALGORITHM

Neural networks are computational models of the biological brain. Like the brain, a neural network comprises a large number of interconnected neurons. Each neuron is capable of performing a simple computation [8]. Artificial Neural Networks (ANN or simply NN) on the other hand, are made up of artificial neurons interconnected to each other to form a programming structure that mimics the behaviour and neural processing (organization and learning) of biological neurons. Neural networks are basically composed of input, hidden layers, output parameters and components which have ability to learn eventually by tuning the weight functions of the parametric model. The neurons are connected by weighted links passing signal from one neuron to another. An intermediate layer couples the input and output signals together, propagating the input signals along a set of connections from the input to the output [9]. The output signal is transmitted through the neurons outgoing connection. The outgoing connection will splits in a number of branches that transmit the same signal. The outgoing branches terminate at the incoming connections of other neurons in the network.

Neural network is renowned for the ability of non-linear reflection, and could simulate the input and output of a complex system [10]. The advantage of neural networks over statistical models is that it does not require a priori knowledge of the underlying distributions of the observed process. Therefore, the neural networks offer an attractive choice for modelling the predictor. Neural network has the ability to classify information and for pattern recognition and has been used to classify modulation types in signals with great accuracy. It can understand how many other radios are nearby, types of communication which is of great use in determining the optimization [9].

A typical artificial neuron and the modelling of a multilayered neural network are illustrated in Fig. 1. Referring to Fig 1, \( x_1 \ldots x_n \) is considered to be unidirectional inputs, which are indicated by arrows, and the signal flows towards neuron’s output \((O)\). The neuron output signal \( O \) is given by the following relationship:

\[
O = f(net) = f\left(\sum_{j=1}^{n} w_j x_j\right)
\]  
(1)
Where $w_j$ is the weight vector, and the function $f(\text{net})$ is referred to as an activation (transfer) function. The variable ‘net’ is defined as a scalar product of the weight and input vectors,

$$\text{net} = w^T x = w_1 x_1 + \cdots + w_n x_n$$  \hspace{1cm} (2)

where ‘T’ is the transpose of a matrix, and the output value $O$ is computed as

$$O = f(\text{net}) = \begin{cases} 1 & \text{if } w^T x \geq \theta \\ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (3)

where $\theta$ is called the threshold level; and this type of node is called a linear threshold unit.

![Architecture of a Neural Network (NN)](image)

Fig. 1 Architecture of a Neural Network (NN)

Learning in NNs is achieved through particular training algorithms which are expanded in accordance with the learning laws, assumed to simulate the learning mechanisms of biological systems [11]. Neural networks have to be configured such that the application of a set of inputs produces the desired set of outputs. This can be achieved by properly adjusting the weights. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. This process is called learning or training. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance with the chosen learning algorithm. Learning can be generally distinguished between supervised and unsupervised learning. In supervised learning, the neural network is fed with teaching patterns and trained by letting it change its weights according to some learning rule, called back-propagation rule. It is a massively parallel, interconnected network of neurons. The neurons are organized into layers with no feedback or lateral connections.

The training algorithm used in this work is the Levenberg-Marquardt (LM) algorithm, which is a variation of Newton’s method that was designed for minimizing functions that are sums of squares of nonlinear functions.

3. PROBABILISTIC NEURAL NETWORK (PNN) ARCHITECTURE

Probabilistic Neural Network (PNN), first proposed by Donald F. Specht [12] is the nearest neighbor classifiers to the complex domain neural network. This network provides a general solution to pattern classification problems, called Bayesian classifiers [13, 14]. PNN is a feed-forward neural network with a complex structure and predominantly a classifier since it can map any input pattern to a number of classifications. PNN has become an effective tool for solving many classification problems [15, 1, 16, 17, and 18].

Network structure determination is an important issue in pattern classification which is based on PNN. In this study, a supervised network structure determination algorithm is discussed. Despite its complexity, PNN merely has a single training parameter. This is a smoothing parameter of the Probability Density Functions (PDFs) which are utilized for the activation of the neurons in the pattern layer. Thereby, the training process of PNN solely requires a single input-output signal pass in order to compute network response.

The PNN [19] architecture is composed of many interconnected processing units or neurons organized in successive layers often used in classification problems. When an input is present, the pattern layer computes the distance from the input vector to the training input vectors which produces a vector where its elements indicate how close the input is to the training input. The summation layer sums the contribution for each class of
inputs and produces its net output as a vector of probabilities. At last, compete transfer function on the output of the third layer picks the maximum of these probabilities, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes in the output layer.

The layered structure of a PNN is as shown in the Figure 2.

For PNN networks [19] there is one pattern neuron for each category of the target variable. The actual target category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron’s category. The pattern neurons add the values for the class they represent. This is carried out in summation layer. The output layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

The summation layer consists of K nodes; each summation node receives the outputs from pattern nodes associated with a given class. The summation layer neurons compute the maximum likelihood of pattern being classified into by summarizing and averaging the output of all neurons that belong to the same class given by

\[ p_i(z) = \frac{1}{(2\pi)^{\frac{d}{2}} N_i} \exp\left[ -\frac{(z - z_{ij})^T (z - z_{ij})}{2\sigma^2} \right] \]  

Where, \( c \) denotes the dimension of the pattern vector \( Z \), \( \sigma \) is the smoothing parameter and \( Z_{ij} \) is the neuron vector. Pattern layer contains one neuron for each case in the training data set. It stores the values of the predictor variables for the case along with the target value. A hidden neuron computes the Euclidean distance of the test case from the neuron’s center point and then applies the RBF kernel function using the sigma values and produces a vector whose elements indicate how close the input is to a training input. Gaussian function is often chosen as the activation function, combined with a radial basis function in the pattern layer.
\[ \text{CL}_i^*(z) = \arg \max \{ p_i(z) \}, \quad i = 1, 2, \ldots, x \quad (6) \]

Where, \( \text{CL}_i^*(z) \) denotes the estimated class of the pattern and \( x \) is the total number of classes in the training samples.

The chief advantages of PNN are high-speed training, an inherently parallel structure, assured to converge to a best possible classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining [20]. PNN learns more quickly than many neural network models and success on a variety of applications. On the other hand, the main disadvantages are it is not as general as back-propagation, requires large memory, slow in execution of the network and requires a representative training set compared to other types of NNs.

4. COMPARISION BETWEEN NN AND PNN

ARCHITECTURE RESULTS

The proposed work based on NNs, motivated by the fact that NNs are widely different from conventional information processing as they have the ability to learn from the prior data, thus being also able to perform better in cognitive tasks. Two NN based learning schemes have been discussed here, the basic NN and the PNN. While the former one aims at predicting channel state by such learning schemes and apply them into future cognitive radio based systems, the latter one addresses that such a learning scheme should be flexible in incorporating further information in the learning process, which can be a objective merit to the process. The proposed NN-based schemes concern the channel state prediction of a specific radio configuration through training process. In order to proficient, the cognitive radio networks must be able to select all the available channel states and to train without exception. This could be implemented by deploying multiple parallel training neural networks. Furthermore, it must be noted that, the NN-based channel prediction can be further fed with other information that might crucially affect the throughput, idle channel prediction for secondary user etc. This could be subject of our research.

Learning is a continuous process during which, the NN’s parameters are adapted according to the gravitational search algorithm. In order to increase the validity and robustness, NNs should be deeply explored especially taking into account more realistic input time-series and environment situations. In conclusion, cognitive radio systems have gained extremely high attention from the wireless research world in the recent years, as well as they will do in the upcoming years, we advocate for implementing learning mechanisms like the ones presented in this paper, to assist the cognitive radios in deciding for their operating radio configuration.

In this work, we presented an experimental evaluation of the performance of PNN and NN. We performed a comparative study of PNN and the NN learning technique and, PNN outperformed from the evaluation criteria adopted. This study presented a new method of hybridizing of artificial neural networks with gravitational search algorithm. Although the obtained results have acceptable accuracy but increasing the number of training data can improved the error function. Future work can be focused on comparing the effect of changing the type of neural networks or optimization techniques, on minimizing the error function.

Figures 3 to 5 gives the comparative plot for NN and PNN. The comparison of our technique is made with respect to HMM, LM based NN [21, 22, 23]. The results show the throughput, SU and SU_{imp} by varying the number of channels from two to ten. Fig.3 shows that the value of the throughput increases with the number of channels. Three, five and nine channel states have been considered, each with 100 time slots and the figures are shown in 3a, 3b and 3c respectively. Fig. 4 shows that SU decrease with increase in number of channels. We can observe that PNN technique has achieved higher values for SU. Fig. 5 shows that the SU_{imp} increases with number of channels. Higher SU and SU_{imp} values show the effectiveness of the technique. The highest SU and SU_{imp} values achieved by our technique are about 0.585 and 0.52 respectively.
5. SUMMARY AND CONCLUSIONS

Despite numerous research efforts in probabilistic neural networks, there has been an improvement in spectrum sensing in channel prediction is concerned. In this study, a supervised PNN structure determination algorithm has been proposed. We have chosen the PNN because of its implementation simplicity and high computational speed in the training stage, when compared to others algorithms. A key feature of this supervised learning algorithm is that the requirements on the network size and training of the predictive channels are directly incorporated in the methodology. As a consequence, the proposed algorithm often leads to a fairly effective network structure with satisfactory...
classification accuracy. This paper also introduces and evaluates learning schemes that are based on NN and can be used for discovering the performance (e.g. throughput) that can be achieved in a cognitive radio networks. So rate of channel prediction can be used to determine the efficiency of the proposed training algorithm. In order to design and use an appropriate neural network structure, performance analysis has been done in simulation environment using MATLAB. The results have been compared and discussed in order to show the benefits of artificial neural network based learning schemes into cognitive radio systems.

REFERENCES


BIOGRAPHY

Pavithra Roy P. obtained her Bachelor’s degree in Electronics and Communication Engineering from Jawaharlal Nehru Technological University, Hyderabad, AP, India. Then she obtained her Master’s degree in Electronics and Communication Engineering with specialization in Digital Electronics and Communication Systems from the Jawaharlal Nehru Technological University, Anantapur, AP, India. Currently, she is an Assistant Professor at the Faculty of Electronics and Communication Engineering, Vemana Institute of Technology, Bangalore, India. Her specializations include Communication Systems, Logic Design and Neural Networks. Her current research interests are Wireless Communications, Cognitive Radio Systems, and Spectrum Utilization.

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