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CHANNEL STATE PREDICTION IN A COGNITIVE RADIO NETWORK USING NEURAL NETWORK LEVENBERG-MARQUARDT ALGORITHM

Pavithra Roy P[1], Dr. Muralidhar M[2]

[1] Assistant Professor, Dept. of Electronics and Communication Engg.,
Vemana Institute of Technology, Bangalore, India. E-mail: pproy2k1@yahoo.com

[2] Principal,
Sri Venkateswara College of Engg. & Technology (Autonomous), Chittoor, India.

ABSTRACT

Spectrum scarcity is one of the main and most challenging issues for the development of new wireless communication technologies. Cognitive Radio (CR) provides the ability to utilize the potential of unused and/or underutilized spectrum in an opportunistic manner. CR is a key enabling technology for dynamic spectrum access. Prediction of idle slots of different channels based on the past information allows a CR to select the best channels for control and data transmission. Majority of cognitive radio research is aimed on methods that use instantaneous information about the environment for dynamic performance. In spectrum sensing, CR users sense the Primary User (PU) spectrum occupancy status and recognize the spectrum holes in the licensed bands. Secondary users sense their environment and respond to probable changes in spectrum availability in an opportunistic way. Such an approach can result in a bad channel selection since the system randomly selects channels that may be frequently used by PUs if that channel is available during the sensing time. A CR predicts how long the channels are going to be idle and selects the longest idle slot for secondary use. The objective of the proposed work is to implement the Neural Network Levenberg-Marquardt (NNLM) algorithm which is specifically designed to minimize such anomalies. NNLM gives the best performance in the prediction of channel states compared to back-propagation algorithms. Simulations show that the proposed classification method predicts the channel effectively and outperforms the random channel selection methods.

Key words: Cognitive radio, channel state prediction, primary users, secondary users, Neural Network Levenberg-Marquardt (NNLM) algorithm

1. INTRODUCTION

Wireless communication has been the fastest growing segment of the communications industry in the last decade. With the incredible growth in the number of wireless systems and services, the availability of high quality wireless spectrum has become severely limited. This has lead to a belief that the spectrum is a scarce resource and it is difficult to find spectrum for new applications. The real problem is not the spectrum scarcity but the inefficiency in the usage of spectrum. CR is a promising technology for overcoming the apparent spectrum scarcity problem, as well as improving communications efficiency. It has been described as an intelligent wireless communication device capable of adapting and reconfiguring itself to satisfy the needs of the end-user. Channel status prediction is important to cognitive radio networks because it can greatly save the sensing energy and help the secondary users to exploit the spectrum holes more efficiently. A reliable channel status prediction mechanism should ensure a lower probability of wrong predictions of the channel status. As the statistics of channel usage in cognitive radio networks are difficult to be determined, we rely on adaptive schemes which do not require such *a priori* knowledge. We have investigated two such adaptive schemes for channel status predictor design, a novel NNLM predictor and a Hidden Morkov Model (HMM) predictor. A qualitative analysis of the two prediction schemes has been presented using various simulations. We have also presented the issues regarding the design of the Multi Layer Perceptron (MLP) network and the HMM as channel status predictors. In cognitive radio terminology, a *primary user (PU)* is defined as a legacy user or a licensed user who has higher rights on particular part of spectrum.

On the other hand, unlicensed cognitive users with lower priority are defined as *secondary users (SUs).* A SU can access spectral resources of a PU when the PU is not using them. However the SU has to vacate the frequency band as soon as the PU becomes active in order that negligible (or no) interference is caused to the PU. Such opportunistic access of the PU resources by the SUs is called as dynamic spectrum access. A SU can opportunistically utilize different spectrum holes corresponding to different PUs in order to satisfy its bandwidth requirement without causing interference to the PUs as shown in Figure 1.

The idea of cognitive radio is that spectrum licensed to primary users may be used in an unlicensed fashion by

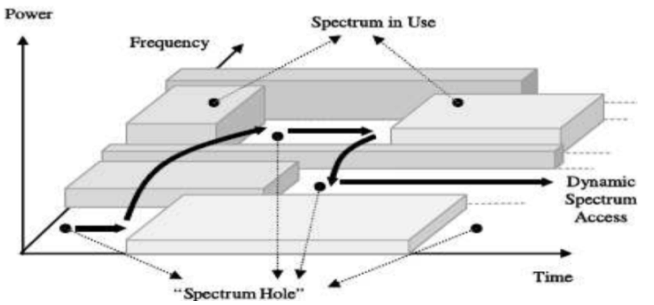

Figure 1: Spectrum holes corresponding to different PUs

secondary users, if these secondary users do not create harmful interference for the primary users. Therefore, a cognitive radio needs to continuously observe and learn the environmental parameters, identify the primary requirements and objectives of the user, and appropriately decide upon the transmission parameters in order to improve the overall efficiency of the radio communications. One way to sense the spectrum is by scanning the corresponding band for some time and detect whether any primary signal is present. If no signal is detected, which is a condition known as *vacant frequency* or *spectrum hole*, it may be concluded safe to begin transmission at a small-predetermined power [1].

In last decade, Intensive work on spectrum sensing in cognitive radio has been reported. CRs provide the ability to use the transmission spectrum more efficiently without causing interference. Interference is controlled by having the cognitive SUs be aware of the environment (e.g., through channel sensing) and adapt their transmission strategies accordingly. An overview of cognitive radio systems and the challenges in this area can be found in [2]-[4]. To ensure the fundamental requirement interference-free communication, the cognitive radio must frequently sense all degrees of freedom, which include time, frequency and space [5], while minimizing the time in sensing [6]. Spectrum sensing has been observed as a key enabling functionality to ensure that cognitive radios do not interfere with primary users [6-11]. If the activities of the primary user is not detected reliably can lead to degradations in the estimation of the channel conditions, such as the primary users are detected as active even though they are idle etc., and thus deteriorates the channel estimation. After performing the sensing and estimation tasks, SUs initiate the data transmission phase. In order to identify the maximum throughput under such constraints, the effective capacity as a performance metric is employed [12]. Effective capacity analysis of wireless systems has gained much interest recently [13, 14]. The cognitive transmission under quality of service (QoS) constraints is studied [15] and channel sensing is performed initially to detect the activities of primary users over a multiple frequency bands and the cognitive transmission is carried out under QoS constraints and interference limitations [16].

Initially, before using the channel, SUs have to detect the activities of the primary users. Among different channel detection techniques, sensing-based access to the channel is superior because of its low employment cost and compatibility with the legacy of licensed systems [17]. Q. Zhao et.al. developed an optimal strategy for opportunistic spectrum access [18, 19]. Moreover, H. Jiang et.al. [20] focused on the optimal sensing order problem in multi-channel cognitive medium access control with opportunistic transmission, and studied the problem of maximally utilizing the spectrum opportunities in cognitive radio networks with multiple potential channels. One of the early studies on channel training was conducted by Cavers who provided an analytical approach to the design of pilot-assisted modulations [21, 22]. These pilot-assisted transmission (PAT) strategies, which multiplex known training symbols with the data symbols, can be used for channel estimation, receiver adaptation, and optimal decoding [23]. In prediction based spectrum mobility [24-26], a CR user predicts the appearance time of PUs, and evacuates the channel before the start of the PU transmissions.

CR is a technology that enables secondary users to discover and access the spectrum holes in the licensed bands. The CR technology includes four major functions, which are presented in Figure 2.

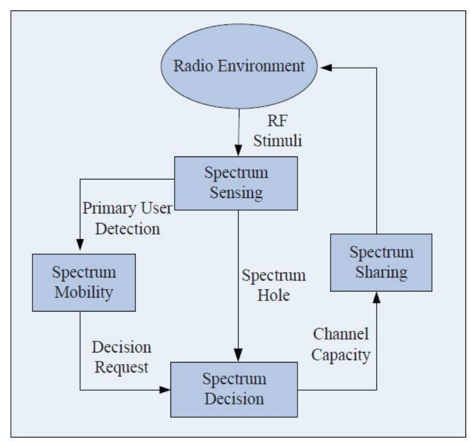

Figure 2: Operation of the cognitive radio functions

The operation of the CR functions shown in Figure 2 can be described as follows. A CR user sequentially senses the spectrum bands and constructs a spectrum pool consisting of all the discovered spectrum holes in the spectrum sensing stage, and selects a channel from the pool for its own transmissions in the spectrum decision stage. In order to enhance the channel capacity, the CR user may share the available channel with other CR users via appropriate spectrum sharing policy. Moreover, the CR user must evacuate its occupied channel upon the return of the primary users according to a spectrum mobility policy, to guarantee the priority of the primary users and protect the PU transmissions.

A MLP is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output. In MLP based prediction [27, 28], the input data is the history observations while the output is the prediction of the future states. The main challenge in multilayer perceptron neural network based prediction is the training of the model, namely changing connection weights of the graph. The training process can be described as follows: 1) process each piece of observation and produce corresponding output; 2) calculate the error of each output compared with the expected value; 3) adjust the connection weights by minimizing the error in the entire output. After the training process, prediction can be made by providing the newest observation as the input to the MLP model. Tumuluru et al. [27] applied the MLP based prediction method for spectrum sensing in cognitive radio networks. In their approach, each CR user predicts the future channel states by using a MLP base predictor and senses only those channels that are predicted to be idle. Such a targeted spectrum sensing can reduce the energy consumption of the CR users.

In spectrum sharing, CR users may join at different times with different bandwidth demands and QoS requirements. Assigning appropriate spectrum bands to the burst heterogeneous CR service requests may lead to considerable time delays, which results in low efficiency in traditional spectrum sharing policies. Carrier Sense Multiple Access based traditional spectrum mobility policy always results in transmission collisions since the CR user does not evacuate its occupied channel until the appearance of the PU is detected. To overcome these shortcomings, prediction based techniques have been extensively studied. In prediction based spectrum sensing [29, 30] a CR user can skip the sensing duty on some channels that are predicted to be busy, thus reducing the sensing time and energy consumption. In prediction based spectrum decision a CR user predicts the quality of the channels in terms of the idle probabilities, idle durations, and other properties, and then selects a high quality channel for sensing and accessing to increase the efficiency of its dynamic spectrum access.

2. LEVENBERG-MARQUARDT (LM) METHOD

The LM algorithm is the most widely used optimization algorithm. It outperforms simple gradient descent and other conjugate gradient methods in the solution of a wide variety of problems [31]. The LM algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real valued functions. . It is fast and has stable convergence. In the artificial neural-networks field, this algorithm is used for training networks. The LM algorithm provides a nice and optimal comprise between the speed of Newton's method and the convergence of the Steepest Descent method. When the current solution is far from the correct one, the algorithm behaves like the Steepest Descent method, slow, to converge and when it is close to the correct solution, it uses the Gauss-Newton method. It has become a standard technique for solving nonlinear least-squares problems and widely adopted in a board spectrum of disciplines.

The neural network that was used for this paper is the feed-forward neural network. MLPs which are capable of finding solutions on a much wider range of problems were used in this paper. Training a feed forward network is an iterative process that involves repeatedly presenting the training set (which contains exemplar patterns with known target outputs) to the network. After each iteration, the network weights are adjusted so that the total error for all patterns is gradually reduced. This type of training is known as supervised learning and the algorithm for adjusting the network weights is the training method. We choose more advanced training methods i.e. the NNLM method as it trains fast with fewer training iterations than back propagation. The MLP consists of three types of layers. The first layer is the input layer and corresponds to the problem input variables with one node for each input variable. The second layer is the hidden layer used to capture non-linear relationships among variables. The third layer is the output layer used to provide predicted values.

Let the function to be minimized be denoted as $Fn(v)$ and it is minimized with respect to the parameter vector denoted as v. The technique can be given by:

$$\Delta v = -[\nabla^2 Fn(v)]^{-1} \nabla Fn(v) \qquad (1)$$

Here, $\nabla^2 Fn(v)$ is the Hessian matrix and $\nabla F(a)$ is the gradient matrix. The gradient matrix is taken as the sum of squares of the error function given by

$$Fn(v) = \sum_{i=1}^{N_c} e_i^{\,2}(v) \qquad (2)$$

Where $\nu = [\nu_1, \nu_2 \dots \nu_N]$ consists of all weights of the network, 'e' is the error vector comprising the error for all the training examples. When training with the LM method, the increment of weights $\Delta\nu$ can be obtained as follows:

$$\Delta v = [J^T(v)\,J(v) + \mu I]^{-1} + J^T(v)e(v) \qquad (3)$$

Where J is the Jacobian matrix, μ is the learning rate which is to be updated using the β depending on the outcome. In particular, μ is multiplied by decay rate β ($0<\beta<1$) whenever $F_n(\nu)$ decreases, whereas μ is divided by β whenever $F_n(\nu)$ increases in a new step[32].

The pseudo code for LM training process can be explained in the following steps:

1. Initialize the weights and parameter μ.
2. Compute the sum of the squared errors over all inputs $F_n(\nu)$.

3. Solve (2) to obtain the increment of weights Δν.
4. Re-compute the sum of squared errors $F_n(\nu)$.Using $\nu + \Delta\nu$ as the trial ν, and judge ,

IF trial $F_n(\nu) < F_n(\nu)$ in step 2
THEN $\nu = \nu + \Delta\nu$
$\mu = \mu.\beta$ ($\beta = .1$)

Go back to step 2
ELSE
$\mu = \mu/\beta$
Go back to step 4
END IF.

3 RESULTS AND DISCUSSION

In this section, the novel Neural Network Levenberg-Marquardt (NNLM) algorithm was evaluated by training simulator and assessed with existing methods. The simulations for analyzing the channel prediction with the proposed techniques were done on MATLAB. The main target of these simulations was to compare the operation performance of the three techniques. The simulation results are shown in Figure 3 and Figure 4 and Figure 5. The algorithms described in the previous section were tested for sensing number of idle slots from the total number of channels (for Secondary User (SU)). The channel prediction comparison among the three methods considered is illustrated in Figure 3. The same data was applied to all three algorithms for comparison. The comparison shows that the NNLM method gives the best prediction rate which proves the efficiency of the proposed technique. Similarly, SU_{pred} plot is shown in figure 4. Here, SU_{pred} can be defined as the ratio of the difference between the number of slots sensed to the number of slots predicted to the total number of channels. NNLM method gives the better channel prediction rate when compared to the HMM method. Finally, the comparison of these two parameters SU and SU_{pred} for NNLM is shown in figure 5. The plots are made by varying the number of channels from 3 to 10. It can be observed that SU decreases with increase in number of channels and SU_{pred} increases with increase in number of channels. In the majority of the simulations, the algorithms converged to points for which the value of the objective function was very close to zero.

4. CONCLUSIONS

Prediction is a promising approach for better realization of cognitive radio networks. Extensive research has been performed on various prediction techniques and applications. However, effort is still needed to design prediction based spectrum sharing methods, provide long-term accurate spectrum prediction, and devise PU activity map prediction schemes. The requirement of high precision spectrum sensing plays important role in the proper utilization of the spectrum. In real time analysis the true path of the states is hidden to the SU and only the data available to the SU is the sensed data. Hence, the Spectrum Sensing is prone to errors in the form of Miss-Detection (MD) and False Alarm (FA).

Therefore, here we exploit these probabilities to frame the spectrum sensing problem into a NNLM paradigm. We have used neural network based technique for implementation of the Levenberg-Marquardt model. Finally, we have performed MATLAB simulations to illustrate the prediction accuracy of the NNLM algorithm. We have simulated the NNLM algorithm for channel prediction with varying channel states .The comparative analysis is carried out by comparing proposed technique output to HMM and random techniques. The highest SU and SU_{pred} values are achieved by proposed NNLM model.

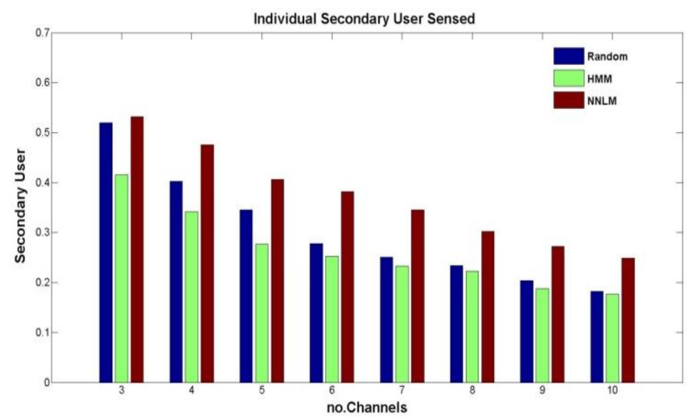

Figure 3: Channel prediction for secondary user with varying channel state

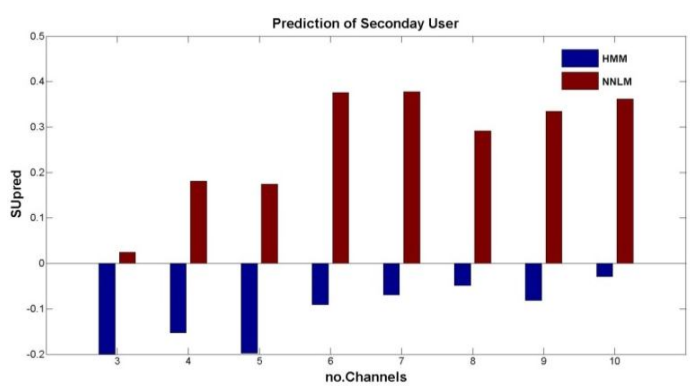

Figure 4: Channel prediction for secondary user with varying channel state

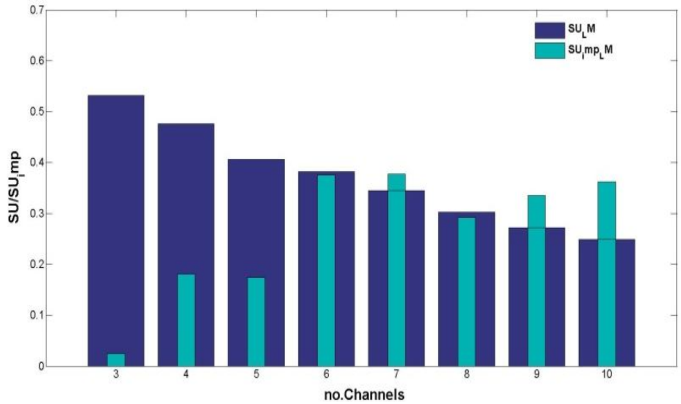

Figure 5: Channel prediction for secondary user with varying channel state

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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.

Dr. Muralidhar M. (Muralidhar Mahankali.) received B.E., M.E. and Ph.D degrees from Sri Venkateswara University, Tirupati, Andhra Pradesh, India. He worked in different cadres in the department of Electrical & Electronics Engineering in Sri Venkateswara University, Tirupati, Andhra Pradesh, India from 1977 to 2011. Currently he is working as Principal and Professor in EEE in Sri Venkateswara College of Engineering & Technology (Autonomous), Chittoor, Andhra Pradesh, India. His research interests are Wireless sensor networks and heterogeneous wireless networks. He is a senior Member of the Institution of Engineers (India) and a Member of the Chartered Engineers (India).