Prediction of Spectrum based on Improved RBF Neural Network in Cognitive Radio

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Abstract: Spectrum prediction is a key technology of cognitive radio, which can help unlicensed users to determine whether the licensed user's spectrum is idle. Based on radial-basis function (RBF) neural network, this paper proposed a spectrum prediction algorithm with K-means clustering algorithm (K-RBF). This algorithm could predict the spectrum holes according to the historical information of the licensed user's spectrum. It not only increases the veracity of spectrum sensing, but also improves the efficiency of spectrum sensing. Simulation results showed that this prediction algorithm can predict the spectrum accessing of the licensed user accurately and the prediction error is only one-third of that of the RBF neural network.

1 INTRODUCTION

The electromagnetic spectrum has been exclusively allocated to different wireless services by government, although some of the frequency bands in the spectrum are unoccupied most of the time or only partially occupied. How to maximize the use of the existing spectrum resources is an urgent problem to be solved. Cognitive radio (CR) is a kind of intelligent spectrum sharing technology, which can rely on artificial intelligence support to adjust the transmission parameters (such as transmission power, data rate, carrier frequency, etc.). CR can effectively use idle spectrum and greatly reduce the restriction to the development of wireless technology by the spectrum and the limitation of bandwidth.

CR network is composed of two parts of the users – licensed user (also known as primary user) and unlicensed user (also known as second user). In each time slot, the unlicensed user must perceive the short-term activities of the licensed user and access slot when it is idle (the idle time slot is also known as spectrum holes). To minimize the interference to licensed users, unlicensed users need a reliable spectrum sensing mechanism. Spectrum prediction is important to effective spectrum of CR network and has become a hot topic in CR. A prediction model using sliding window was established to predict licensed users' future spectrum activity [1]. This model sets a threshold value through the adaptive filter. The frequency band which is lower than the threshold will be set to be unreliable and do not allow unlicensed users to access this band. A multilayer perceptron for spectrum prediction was proposed [2]. However, the multilayer perceptron uses traditional unconstrained minimization method to achieve minimization of the error function. Therefore, it inevitably has local minima problem. Subsequent studies have proposed ON-OFF, Blackman window, POMDP, and other prediction mechanisms (Federal Communications Commission, 2002); (Acharya et al., 2006); (Jianli et al., 2011). In (Marko et al., 2008), a dynamic spectrum access algorithm based on probably density estimation was proposed to predict channel state with flexibility and availability.

However, when the CR node sensing the spectrum, it will detect the whole spectrum concerned every time. It will consume a lot of network resources. We addressed the problem in this paper and proposed a spectrum prediction algorithm using radial-basis function (RBF) neural network based on K-means clustering algorithm (K-RBF). In the algorithm, the spectrum holes are predicted according to the licensed users's historical information. Then, appropriate spectrum bands are chosen for the unlicensed users to detect. It can

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greatly reduce the resources consumed in spectrum sensing.

The rest of the paper is organized as follows. In Section II, we present the system model of spectrum prediction with RBF neural network. In Section III, we propose the improved prediction algorithm of spectrum. In Section IV, we provide the simulations for the improved prediction algorithm and demonstrate the effect of spectrum prediction. Finally, Section V concludes this paper.

2 SYSTEM MODEL

Whether the licensed user's spectrum is idle can be modelled as a binary series prediction problem. We design the binary series predictor using neural networks. Neural networks are nonlinear parametric models which create a mapping function between the input and output data.

The most basic form of RBF neural network is a three-layer forward network, which includes the input layer, the hidden layer, and the output layer, as shown in Figure 1. The input layer has some source nodes (perception units) connecting to the external environment, while the hidden layer has a variable number of neurons (the optimal number is determined by the training process). The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the centre of the neuron. The output layer produces response to the input mode.

Let us assume that it has N input nodes, M hidden nodes, and one output node. Consider that in the RBF neural network structure, the network input vector is

$$\boldsymbol{X} = \left[x_1, x_2, \cdots, x_N\right]^T \tag{1}$$

The network radial base vector is

$$\boldsymbol{H} = \left[h_1, h_2, \cdots, h_M\right]^T \tag{2}$$

where h_j is the Gaussian basis function

$$h_j = \exp\left[\frac{\left\|\boldsymbol{X}-\boldsymbol{C}_j\right\|^2}{2b_j^2}\right]\left(j = 1, 2, \cdots, M\right) \tag{3}$$

and C_j and b_j are the center and width of the $j-th$ neuron in the hidden layer, respectively, $\|.\|$ denotes the Euclidean distance,

$$\mathbf{C}_j = \left[c_{j1}, c_{j2}, \cdots, c_{jN}\right]^T \tag{4}$$

The network base width vector $\boldsymbol{B}$ can be given as

$$\boldsymbol{B} = \left[b_1, b_2, \cdots, b_M\right]^T \tag{5}$$

The network weight vector is

$$\boldsymbol{W} = \left[w_1, w_2, \cdots, w_M\right]^T \tag{6}$$

The output of the network is

$$y_m\left(k\right) = w_1h_1 + w_2h_2 + \cdots + w_M h_M \tag{7}$$

The RBF is used as a hidden unit "base" and constitutes the hidden layer space. The input vector is transformed in the hidden layer and low-dimensional model input data are transformed to the high-dimensional space, making the linear inseparable problem in low-dimensional space become linear separable in high-dimensional space. However, the initial values of the centers of hidden layer nodes and the width of base function will affect the prediction ability of the network. Therefore, selecting appropriate values for the two initial parameters can improve the prediction accuracy of the network. In this study, we have used K-means clustering algorithm to obtain the values of the centers of the hidden layer nodes and the width of the base function, then construct and train a more accurate RBF neural network.

3 SPECTRUM PREDICTION

3.1 K-means Clustering Algorithm

K-means algorithm (Zhao et al., 2007) is a clustering algorithm based on the sum of error square criterion. First, it randomly selects K points from the data as the initial cluster center. Then, it calculates the distance from each sample to each center of the clusters and assigns samples to categories whose cluster center is nearest to them. Subsequently, it calculates the average of each newly formed cluster data to obtain a new cluster center. If there is no change in the adjustments between the adjacent two cluster centers, then it is the end of sample adjusts and clustering function is converged. If there are some changes, then the allocation and update steps are repeated until the clustering function converges. A characteristic of this algorithm is to examine whether the classification of each sample is correct in each iteration. If the classification is not correct, then it should be adjusted. After adjusting the whole

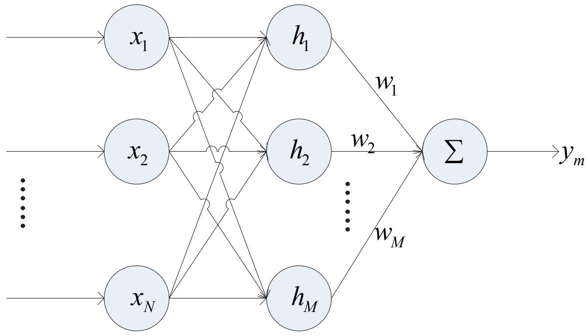

Figure 1: RBF neural network structure.

sample, the cluster center is modified, and the next iteration is carried out.

3.2 K-RBF Prediction Algorithm

Assume that K is the number of iterations of the network, the K^{th} iteration clustering center is $c_1(k), c_2(k), \cdots c_M(k)$, and the corresponding clustering domain is $w_1(k), w_2(k), \cdots w_M(k)$. Through the K-means algorithm, the center of hidden layer nodes $\boldsymbol{C}$ and base function width $\boldsymbol{B}$ of RBF neural network can be determined.

First, the first M samples are chosen from the whole samples input as the initial cluster centers. The center values of the M samples cannot be same. Then, set $k = 1$. The distance d from the selected samples and the cluster centers is calculated as

$$d = \left\| X_j - c_i(k) \right\|, i = 1, 2, \cdots, M, j = 1, 2, \cdots, N \quad (8)$$

where X_j is the input sample. The samples are assigned based on the minimum distance rule. When $i = \min_i \left\| X_j - c_i(k) \right\|, i = 1, 2, \cdots, M$, X_j is assigned to category i ($X_j \in w_i(k)$). After classification, the new cluster centers of all categories are recalculated as

$$c_i(k+1) = \frac{1}{N} \sum_{x \in w_i(k)} x, \qquad i = 1, 2, \cdots M \quad (9)$$

If $c_i(k+1) \neq c_i(k)$, then the classification is repeated and the steps are updated. If $c_i(k+1) = c_i(k)$, each hidden node's base width b_i is determined according to the distance between each clustering centers. The expression of b_i is

$$b_i = \sigma d_i \quad (10)$$

where d_i is the distance between the i^{th} clustering center from the centers of the other sample data, which is the nearest to i^{th} clustering center, and σ is the overlap coefficient. d_i is expressed as

$$d_i = \min_i \left\| c_j - c_i(k) \right\| \quad (11)$$

Then, the hidden nodes' output is calculated by the Gaussian basis function, according to (3).

The K-RBF prediction algorithm above is summed as following:

(1) Initialization setting. Select the first M input samples from samples. The values of the centers of the h sample cannot be the same. Assume that the number of iterations is $k = 1$.

(2) Calculate the distance d from the selected input samples to the clustering center according to (8).

(3) Classify the input samples X_j according to the minimum distance rule.

(4) Recalculate the new cluster center according to (9). If the two cluster centers are not equal, repeat the classification and the update steps.

(5) Obtain the distance between each cluster centers according to (11), and determine the base width vectors according to (10). The outputs of the hidden nodes are obtained according to (3) and (7).

4 SIMULATION AND ANALYSIS

The channel state is divided into two types: occupation (in the binary sequence using "1") and idle (with "0"). In the simulation, we use the m sequence and Gold sequence to simulate the channel state occupied by licensed user respectively. We took the first 350 data to train the neural network and the last 70 data as the test data to test the neural network. First, we used *m* sequence to simulate. The comparison of the prediction data with the actual data is shown in Figure 2, and the prediction error is presented in Figure 3. They showed that K-RBF can not only accurately predict spectrum occupancy state but the prediction error is also very small.

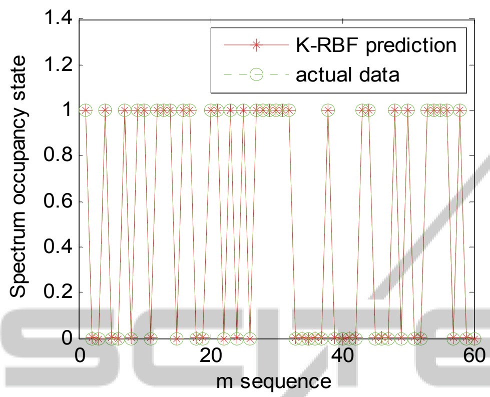

Figure 2: Comparison of prediction data with actual data under *m* sequence.

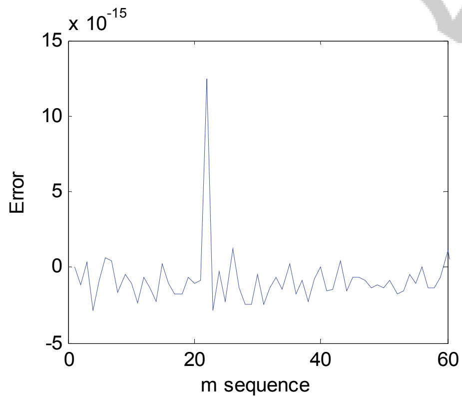

Figure 3: Prediction error of *m* sequence.

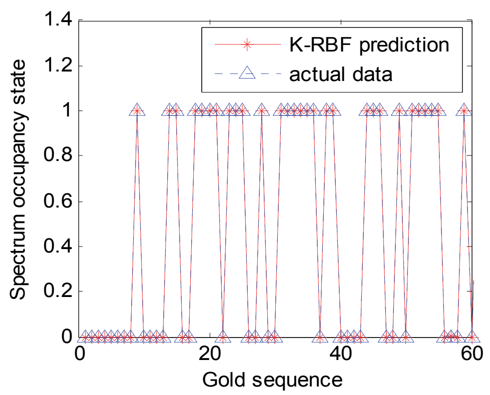

Figure 4: Comparison of prediction data with actual data under Gold sequence.

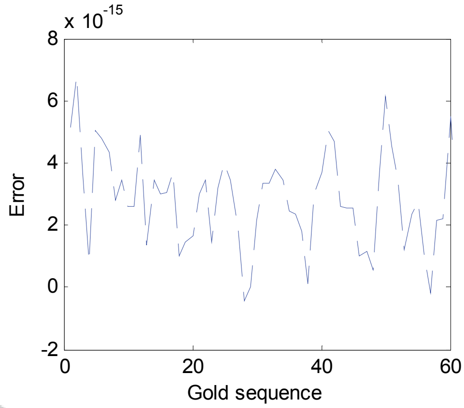

Figure 5: Prediction error of Gold sequence.

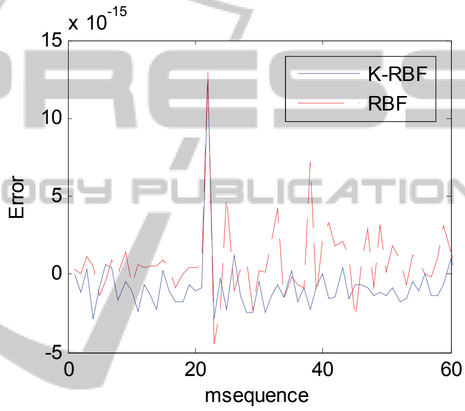

Figure 6: Prediction error comparison.

To verify the robustness of K-RBF algorithm to predict the spectrum occupancy state, we simulated the K-RBF algorithm with Gold sequence also. The comparison of the predicted data and the actual data is shown in Figure 4, and the prediction error is presented in Figure 5.

From the simulation results of Figure4 and Figure 5, it was found that the prediction error of Gold sequence is also very small. It implies that the K-RBF algorithm has the robustness to randomicity of licensed user accessing spectrum.

Figure 6 compares the prediction error of *m* sequence simulated by RBF with K-RBF. It showed that the prediction accuracy of the K-RBF is higher than that of RBF neural network. And, the prediction error of the K-RBF was found to be only one-third of that of the RBF neural network.

5 CONCLUSIONS

In this paper, we proposed a spectrum prediction algorithm: K-RBF algorithm. We used K-means clustering algorithm to obtain the hidden nodes center and base function width of the RBF neural network. Then, we train and form more appropriate neural network. Through simulation, we found that K-RBF algorithm can achieve better predicting precision. Thus, we can use the prediction information to sensing the licensed user spectrum more simply. And, it will reduce the resource consumed.

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