A Novel Spectrum Prediction Algorithm for Cognitive Radio System Based on Chaotic Neural Network *

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Abstract

In the cognitive radio system, the rationalization of spectrum allocation can be improved by the spectrum prediction algorithm. In recent years, the researches of spectrum prediction focus on how to predict channel status. In order to improve spectrum utilization and reduce frequency of channel switching, a novel spectrum prediction mechanism is designed, which use Chaos Neural Network to analyze and predict duration of channel status. The effectiveness of the new mechanism is proved through the extensive simulation.

Keywords: Cognitive Radio System; Chaotic Neural Network; Spectrum Prediction; Channel Status

1 Introduction

Over the past decade, with the increasing demand for wireless application, the problem of wireless spectrum insufficiency is more and more serious; on the contrary, the utilization of some licensed spectrum is always low. How to maximize usage of existing resources is key problem for researchers. However, cognitive radio (CR) technology can solve this problem by an effective scheme [1].

In cognitive radio system, the secondary users (SU) can only use the spectrum not be occupied by the primer users (PU) [2]. These idle spectrums are also known as the spectrum hole. In order not to interfere in PU, a reliable sensing mechanism is essential. Several spectrum sensing mechanisms were proposed in literature [3, 4, 5, 6, 7, 8, 9]. But it consumes a large amount of energy by using simply sensed full spectrum. Thats why the channel status prediction is very

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important. A good prediction mechanism can increase the probability of SU access, decrease the
frequency of channel switching and save the sensor energy. In another word, a channel can be
allocated reasonably with a spectrum prediction.

In recent years, there are not many works in field of spectrum prediction algorithm. Most of
them focus on how to predict the spectrum status (i.e. occupied or idle). For example, some works
based on the idea of linear regression, a binary time series prediction was designed in literature
[10]; a high-order Markov model was proposed in literature [11, 12]; some works designed a
spectrum prediction mechanism based on neural network multi-sensing model [13], but it had
some shortcoming in field of channel status prediction. For example, according to the prediction,
the channel switch to idle, but the idle time is very short. At this point, if it allocates a channel
to SU, it collide with the following PU, and increases frequency of channel switching. On the
other hand, if the channel is occupied by PU, but it is a very short time, and SU switch to other
channels according to this results, it leads to communication channel allocation unreasonable.

In this paper we propose to predict the duration of spectrum status, and design a novel approach
for predicting the duration of spectrum state through chaotic neural network, and then analyze
the performance of prediction mechanism.

2 Prediction Process

SU and CR spectrum access point can also predict the duration of spectrum status, the process
is shown in Fig.1

Fig. 1: System prediction process

(1) The duration of last 2M channel status \( \Gamma = \{ \Gamma_1, \Gamma_2, \ldots, \Gamma_{2M} \} \) for the historical data is
selected, \( \Gamma \) include the duration of \( M \) OFF-states (idle) and \( M \) ON-states (occupied). the
new time series from sampling the data is generated, where \( \Delta t \) is the sampling interval. The
sampling process is illustrated in Fig.2.

Fig. 2: Time series generate process
The set of sampling is \( \mathbf{C} = \{c_1, c_2, \ldots, c_n\} \) \((n\) is the total number of sampling), and the sampling time points set is \( \mathbf{T} = \{t_1^c, t_2^c, \ldots, t_n^c\} \), \( \Gamma_{\text{rem}}^i \) denotes the remaining duration of corresponding state in each sampling point.

\[
\Gamma_{\text{rem}}^i = \Gamma_z - t_i^c, \quad z = 1, 2, \ldots, 2M, \quad \frac{\Gamma_{z-1}}{\Delta t} < i \leq \frac{\Gamma_z}{\Delta t} \tag{1}
\]

So the time-series of the remaining duration of spectrum status is denoted by \( \Gamma_{\text{rem}} = \{\Gamma_{\text{rem}}^1, \Gamma_{\text{rem}}^2, \ldots, \Gamma_{\text{rem}}^N\} \), whose the length \( N \) is \( n \).

(2) The time series \( \Gamma_{\text{rem}} \) are put in the prediction module and the channel information is predicted.

(3) After the true channel information is obtained, which inserts into the historical data, the time window is slidden and then the rolling prediction is done. The process of time window sliding is shown in Fig. 3.

### 3 Prediction Module

As shown in Fig. 1, prediction module reconstruct the phase space based on a chaos analysis about the time series at first, and then make prediction by combining with BP neural network. Prediction module includes two parts: (1) chaotic sub-module; (2) neural network sub-module, which is shown in Fig. 4.
3.1 Chsotic sub-module

The main function of chaotic sub-module: (1) the time series embedding dimension \( m \) and delay \( \tau \) are calculated; (2) the phase space with \( m \) and \( \tau \) are reconstructed; (3) the largest Lyapunov (Lyapunov) exponents \( \lambda \) are calculated; (4) \( \lambda \) determined whether time series is chaos or not.

3.1.1 Calculation of embedding dimension \( m \) and time delay \( \tau \)

In the paper, the C-C method is selected to calculate \( m \) and \( \tau \), the algorithm is shown as follows:

The remaining duration time-series is divided \( \Gamma_{\text{rem}} \), \( i = 1, 2, \ldots, N \) into \( t \) disjoint sub-time series:

\[
\{ \Gamma_{\text{rem}}^1, \Gamma_{\text{rem}}^2, \Gamma_{\text{rem}}^3, \ldots \}, \{ \Gamma_{\text{rem}}^2, \Gamma_{\text{rem}}^3, \Gamma_{\text{rem}}^4, \ldots \}, \ldots \{ \Gamma_{\text{rem}}^t, \Gamma_{\text{rem}}^{t+1}, \Gamma_{\text{rem}}^{t+2}, \ldots \},
\]

(2)

Where, \( l = \frac{N}{t} \) is the length of the sub-time-series. For \( t \) disjoint sub-time series:

\[
S(m, N, r, t) = \frac{1}{l} \sum_{s=1}^{t} [C_s(m, \frac{N}{t}, r, t) - C_s^m(1, \frac{N}{t}, r, t)] \quad (3)
\]

Where, \( C_s(m, \frac{N}{t}, r, t) \) is the correlation integral of each sub-time series, \( m \) is the embedding dimension and \( r \) is the radius.

Then choose the maximum and minimum radius \( r \), the differential is denoted as:

\[
\Delta S(m, t) = \max \{S(m, r, t)\} - \min \{S(m, r, t)\} \quad (4)
\]

After that the following three statistics can be calculated:

\[
\bar{S}(t) = \frac{1}{16} \sum_{m=2}^{5} \sum_{j=1}^{4} S(m, r, t) \quad (5)
\]

\[
\Delta \bar{S}(t) = \frac{1}{4} \sum_{m=2}^{5} \Delta S(m, t) \quad (6)
\]

\[
S_{\text{cor}}(t) = \Delta \bar{S}(t) + |\bar{S}(t)| \quad (7)
\]

The best delay \( \tau \) corresponds to the first zero point of \( \bar{S}(t) \) or the first minimum value of \( \Delta \bar{S}(t) \).

The optimal embedding window width corresponds to the minimum value of \( S_{\text{cor}}(t) \). The \( m \) can be calculated by the embedding window width formulation \( \tau_w = (m - 1)\tau \).

3.1.2 Phase space reconstruction

Phase space reconstruction can restore the dynamics of the attractor. For the time series \( \Gamma_{\text{rem}} \), the phase space \( Y_i \) can be reconstructed by choosing the embedding dimension \( m \) and delay \( \tau \):

\[
Y_i = \{ \Gamma_{i, \text{rem}}, \Gamma_{i+\tau, \text{rem}}, \Gamma_{i+2\tau, \text{rem}}, \ldots, \Gamma_{i+(m-1)\tau, \text{rem}} \} \quad i = 1, 2, \ldots
\]

(8)
3.1.3 Calculation of the largest Lyapunov exponents and determination of the time series chaos or not

The Lyapunov exponents $\lambda$ can be decided whether the time series is chaos or not:
- $\lambda < 0$ denotes the stable fixed points and periodic motion;
- $\lambda > 0$ denotes the chaotic motion;

Many methods can get the value of $\lambda$, in this paper, the wolf algorithm [13] can be chosen to get the value of $\lambda$, and whether the time series is chaos or can be judged.

3.2 BP neural network sub-module

BP neural network has been widely used for its simple structure, multi-adjustable parameters and multi-training methods. BP neural network is the core of the neural network which is a typical feed-forward neural network. It can obtain the non-linear mapping between the input and the output via adjusting input weights. Here the time series can be reconstructed $\Gamma^{\text{rem}}$ and the delay coordinate vector can be got:

$$Y_i = \{\Gamma^{\text{rem}}_{i}, \Gamma^{\text{rem}}_{i+\tau}, \Gamma^{\text{rem}}_{i+2\tau}, \ldots, \Gamma^{\text{rem}}_{i+(m-1)\tau}\}$$

After $h$-steps prediction, the non-linear function can be approximated by BP network:

$$\Gamma^{\text{rem}}_{i+h} = F_h[Y_i]$$

The feed-forward networks keep regulating the input weight vectors and learning samples to determine the quantitative relations between $Y_i$ and $\Gamma^{\text{rem}}_{i+h}$. After network training was complete, the $h$-steps prediction can be done. The specific steps are followed as:

1. The network is built. The embedding dimension $m$ is calculated by chaotic time series and then $m$ is input of number of network.
2. Training process. To input sample sequence obtains the results of output which keep fitting approximation with the following equation (10) until the error is acceptability.
3. Input data is predicted.

4 Simulations

4.1 Simulation parameters and performance evaluation parameters

4.1.1 Simulation parameters

Based on literature [14], the primary user channel can be set ON-OFF model, where $M$ is set to 400, $\Delta t$ is set to 2s, $m = 6$ can be calculated, $\tau = 12$ by the C-C algorithm and the average period is 53 which is calculated by Fast Fourier Transform; finally, $\lambda$ can be calculated as 0.24383 by the Wolf method, Because of $\lambda > 0$, the time series is chaos time series.
4.1.2 Performance evaluation parameters

In this paper, errors (err) and relative errors (relerr) are performance evaluation parameters which are defined as:

\[
\text{err}(x) = \text{pre}(x) - \text{real}(x) \quad \text{(11)}
\]

\[
\text{relerr}(x) = \frac{|\text{pre}(x) - \text{real}(x)|}{\text{real}(x)} \quad \text{(12)}
\]

Where pre(x), real(x) denote predictive value and true value, respectively.

4.2 Chaotic neural network prediction performance analysis

According to the method. After the phase space reconstructed, the time series select appropriate samples and put them into the BP neural network for training. After that the 1300 to 1500 points are chose to do rolling prediction and compare with the true value. Where the training precision (goal) is set to 0.005, embedding dimension \( m \) is 6; here the prediction set is defined as:

\[
C^{\text{pre}} = \{e_i^{\text{pre}}\}, i = 1300, \ldots, 1500. \quad \text{(13)}
\]

Fig. 5: Prediction errors and relative errors of chaos BP network

The prediction errors and relative errors of the chaos BP neural network (chaos BP) is shown in Fig.5, result is shown that prediction error is only between \(-12\) to \(12\) and prediction precision can reach 90%, so the method has a good precision.

4.3 The main influence of predictor analysis

The goal value has greater impact on prediction performance. The results is shown in Figure 6 and Figure 7 by choosing 0.5, 0.05 and 0.005 to analyze the prediction performance. It can be seen from the figure, when error is 0.005, it will obtain the minimum goal and the best prediction
performance. Related with choosing a goal value, in principle, the smaller is the goal value, the better is prediction performance, but when the goal is too small, the training will be failure, because the precision is high, at the same time, the training time will be longer, which is not fit for the cognitive radio which needs the short time for prediction.

5 Conclusion

In spectrum prediction, many literatures focus primarily on prediction the channel status (i.e. occupied or idle). Based on chaotic neural network, this paper design a novel approach by predicting the rest duration of channel status. This approach not only predict the channel status, but also predict the duration of spectrum state. Simulation results show that spectrum prediction algorithm for cognitive radio system based on chaotic neural network outperforms other scheme in existing literature.

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