Wavelet Transform and Artificial Neural Network Based Spectrum Sensing in Cognitive Radio

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Abstract. With the progress and upgrade of wireless telecommunication technologies, the lack of spectrum resources is pretty serious. As a method to improve spectrum utilization, cognitive radio has received widespread attention. The technology of spectrum sensing, one of the most significant parts of cognitive radio, has important research value. The existing spectrum sensing technology is difficult to detect the main user signal at a lower signal-to-noise-ratio (SNR). To solve this problem, wavelet transform and artificial neural network based spectrum sensing in cognitive radio is put forward. The spectrum detection perceptual classifier is designed through the wavelet transform, cyclostationary feature and the artificial neural network. Firstly, the wavelet threshold method is used to process the received signal. The cyclic characteristic value of the processed signal is calculated. Secondly, the eigenvalues are learned and stored through the artificial neural network. Finally, the test data is brought into the trained network for classification. Verifying by simulation experiments, the proposed algorithm has better accuracy and effectiveness than the original method in the low SNR environment.

1. Introduction
As the wireless telecommunication technologies progress and upgrade, the contradiction between the growing spectrum demand and spectrum utilization is becoming increasingly [1]. Cognitive radio technology can effectively improve utilization of spectrum by sensing the available spectrum of the current environment [2]. Spectrum sensing technology, in order to communications from authorized users are not interfered, is one of the most significant parts of cognitive radio. The sensing function should analyse the usage of the frequency band so that find the “spectral holes” for communication. At present, cognitive radio spectrum sensing technology is generally divided into transmitter-based detection, receiver-based detection, interference based detection and so on. The methods based on transmitter detection mainly include cyclostationary feature detection method, energy detection method and matched filtering method [3]. Energy detection does not need to know the prior knowledge of the signal, which is simple to implement. But the ability to adapt to noise is limited [4]. The cyclostationary feature has good detection performance, but it has the disadvantages of high computational complexity and large delay [5]. Although the matched filter method is theoretically superior, it requires the prior information of the primary user (PU) in media access control layer,
which is difficult to implement in a complex and variable wireless environment [6]. Artificial neural network (ANN) algorithm, as one of the fastest development algorithms at this stage, has better fault tolerance [7]. Artificial neural network has the strength of adaptive learning. According to this advantage, it can be combined with wavelet transform and cyclostationary feature, which can enhance the detection probability of the algorithm at low SNR. Therefore, wavelet transform and artificial neural network based spectrum sensing in cognitive radio is put forward in this paper. The received signal is preprocessed by wavelet transform. Then the cyclostationary characteristics of the training samples are extracted, which is applied to ANN. Utilize the advantages of the three methods to enhance the spectrum detection performance at low SNR.

2. Data model
In spectrum sensing, it is assumed that the perceived channel is a non-fading channel. The secondary user uses the local received data to determine whether PU occupies the frequency band. In this case, the spectrum sensing problem can be described as binary hypotheses.

\[ y(t) = \begin{cases} 
  n(t) & \text{if } H_0 \\
  h x_i(t) + n(t) & \text{if } H_1 
\end{cases} \]  

(1)

Where \( n(t) \) is the additive white Gaussian noise (AWGN) in the channel. \( H_0 \) represents that there is no authorized user in this band. \( H_1 \) represents that the authorized user exists within the frequency band. \( y(t) \) is the signal received by the receiver. \( x_i(t) \) is authorized user signal information. \( h \) is the wireless channel gain [8].

3. Algorithm formulation

3.1 Wavelet Transform
Wavelet transform theory has been widely used in wireless signal field. It has a good time-frequency localization capability. In terms of data processing, the performance is very good. In this paper, the signal is preprocessed by using wavelet threshold. If a signal contains noise, the noisy signal is split in many layers when wavelet threshold is used to denoise. Therefore, the noisy signal is decomposed by multiple layers. The modulus of signal wavelet transform coefficient is larger than the modulus of noise wavelet transform coefficient. Choose an appropriate threshold. If the wavelet transform coefficient modulus of the signal is greater than or equal to the threshold, the coefficient is considered to be obtained by signal decomposition. If the wavelet transform coefficient modulus of the signal is less than the threshold value, the coefficient is considered to be derived from noise decomposition. In general, this coefficient is set directly to zero. Finally, the inverse signal is obtained by wavelet inverse transform.

Firstly, wavelet transform is performed on the noisy signal \( y(t) \), and then a set of wavelet decomposition coefficients is obtained. Then, the wavelet decomposition coefficients are processed. The wavelet estimation coefficients are obtained. In this paper, the soft threshold function is adopted.

\[ \hat{w}_{j,k} = \begin{cases} 
  \text{sgn}(w_{j,k})(|w_{j,k}| - \lambda), & |w_{j,k}| \geq \lambda, \\
  0, & |w_{j,k}| < \lambda. 
\end{cases} \]  

(2)

Where \( w_{j,k} \) is the coefficient of the wavelet transform. \( \text{sgn}(w_{j,k}) \) is the sign function of \( w_{j,k} \). \( \lambda \) is the threshold. \( \hat{w}_{j,k} \) the wavelet coefficient after the attenuation.

In this paper, visushrink threshold is adopted.
\[ \lambda = \sqrt{\sigma 2 \ln N} \]  
\[ \sigma = \frac{\text{median} \left| w_{0,1} \right|, \ldots, \left| w_{i, N-1} \right|}{0.6745} \]  

Expression (3) is visushrink threshold. \( \sigma \) is the noise standard deviation, which estimated by (4). \( N \) is the signal length.

Finally, wavelet reconstruction is performed by the wavelet coefficient \( \hat{w}_{j,k} \). The estimated signal \( y(t) \) is obtained, which is the preprocessed signal.

### 3.2 Cyclic spectrum characteristics

Received signal is processed by wavelet threshold. Although some of the noise has been removed from the signal, some of the residual noise remains in the signal. The primary user signal has a cyclic spectrum characteristic that is not available in noise [9]. Therefore, the cyclic spectrum feature can be used to determine spectrum perception. The principle of the algorithm is represented in Figure 1.

\[ y(t) \rightarrow \text{A/D} \rightarrow \text{FFT} \rightarrow \text{Spectral correlation function analysis} \rightarrow \text{Judgment} \]

**Figure 1.** The cyclostationary feature detection

Assume that the received signal contains the signal of primary user, both the mean function \( m_y(t) \) and the autocorrelation function \( R_y(t) \) have periodic characteristics. There is a period \( T \) that satisfies expression (5) and expression (6).

\[ m_y(t) = m_y(t + T) \]  
\[ R_y(t + \frac{T}{2}, t - \frac{T}{2}) = R_y(t + \frac{T}{2} + T, t - \frac{T}{2} + T) \]  

Assume that the Fourier series of signal autocorrelation function is convergent, it can be calculated by (7).

\[ R_y(t + \frac{T}{2}, t - \frac{T}{2}) = E \left\{ y(t + \frac{T}{2}) y^*(t - \frac{T}{2}) \right\} = \sum_{\alpha} R_{y}^{\alpha}(\tau) e^{j2\pi \alpha \tau} \]  
\[ R_y^{\alpha}(\tau) = \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} R_y(t + \frac{T}{2}, t - \frac{T}{2}) e^{-j2\pi \alpha \tau} dt \]  
\[ S_{y}^{\alpha}(f) = \int_{-\infty}^{\infty} R_y^{\alpha}(\tau) e^{-j2\pi f \tau} d\tau \]  

Where \( R_{y}^{\alpha}(\tau) \) is the cyclic autocorrelation function of the signal. (9) is the Fourier transform of (8). \( S_{y}^{\alpha}(f) \) is the spectral correlation function of signal, which is also called the cyclic spectral density function.

\[ S_{y}^{\alpha}(f) = \int_{-\infty}^{\infty} R_{y}^{\alpha}(\tau) e^{-j2\pi f \tau} d\tau = \sigma^2 \delta(\alpha) \]  

In addition, spectral correlation function of noise are calculated by (10). In (10), the spectral correlation function will only peak at \( \alpha = 0 \), and the value is zero in other places. Therefore, the main
user signal is judged build on the frequency domain of the received signal and the value of feature point on the cyclic frequency domain. Figure 2 shows the cyclic spectrum of signal.

![Cyclic Spectrum of Signal](image)

**Figure 2.** The cyclic spectrum of signal

3.3 Artificial neural networks

The cyclic spectrum characteristics of signal is obtained. However, it is obviously impossible to judge the size of the received signal cyclic spectrum by artificial methods. The neural network algorithm can make the unauthorized users have the learning ability, and can accumulate the information of the main user through the training of the neural network, Adaptive real-time detection of the main user signal [10, 11]. In this article, the artificial neural network method is used for classifying cyclic spectrum values of signals. Artificial neural network consists of multiple neurons. The relationship between the input and output of a single neuron is shown in (11).

\[
b = f(\sum_i w_i a_i - \theta)
\]

Where \(a_i\) is the input of the neuron. \(w_i\) is the weight. \(b\) is the output of the neuron. \(\theta\) is the value of the node. \(f\) is the activation function.

The Back-Propagation (BP) algorithm is taken advantage of calculating error in network. The BP algorithm returns the resulting solution and error along the original transfer route. The error is reduced by modifying the connection weights of neurons in each layer. Then turn to forward propagation. Calculate until the error is less than the set value.

4. Simulation and Analysis

This section constructs some simulations to demonstrate the relevant performance of the proposed approach. Assumed that signal of PU is a BPSK signal in AWGN. SNR range is -20dB to 0dB. Assuming that the signal and noise are irrelevant. The frequency of BPSK is 120 Hz. The carrier frequency of the BPSK is 30 Hz. The signal period is 1 s. The number of samples is 2048. The simulation process for BPSK signals is divided into three steps.

Firstly, the received signal is subjected to wavelet transform, and the preprocessed signal is obtained. Then, the preprocessed signal is subjected to feature value extraction. In this paper, the peaks of 2 cyclic spectra and 2 times the cyclic spectrum peaks are used. Finally, four eigenvalues are brought into ANN for training and prediction.
The neural network uses three-layer BP neural network. The quantity of input neurons is 4, and the quantity of hidden layer neurons is 10. The quantity of output neurons is 2. The activation function of hidden layer neuron is sigmoid. The activation function of output layer neuron is relu. The maximum number of training is 600. The learning rate is 0.1. The training data set is 10,000 and the test data set is 5000.

![Figure 3. Training times of wavelet transform neural network.](image1)

![Figure 4. Training times of neural network without wavelet transform.](image2)

From Figure 3 and Figure 4, it shows that neural network with wavelet transform is significantly less trained than neural network without wavelet transform.

![Figure 5. Probability of Detection under different SNR](image3)

From Figure 5, it can be concluded that the detection performance is related to the SNR of the training sample signal. The method proposed in this article is better than the traditional method of spectrum sensing. In the case of low SNR, there is still good detection performance. Compared with the simple neural network, the proposed method has better detection performance under the same signal-to-noise ratio.

5. Conclusion
This paper presents a spectrum sensing algorithm based on wavelet transform and ANN. Because the traditional frequency method is difficult to detect the main user signal at a lower SNR. By combining
the advantages of wavelet transform, cyclostationary detection and artificial neural network, the detection performance of spectrum sensing at low SNR is improved. Compared with other spectrum sensing methods, this method not only can achieve good detection performance at high SNR, but also at low SNR. It solves the problem of difficult detection in low SNR environment. In the future work, combine with wavelet transform and neural network, a better preprocessing methods which can get better detection results is still need to research.

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