High Accuracy Signal Recognition Algorithm Based on Machine Learning for Heterogeneous Cognitive Wireless Networks

Jian Liu, Jibin Wang, and Sani Umar Abdullahi
School of Computer and Communication Engineering, USTB, Beijing 100083, China
Email: liujian@ustb.edu.cn; wjbjekyll@163.com; saniumar.a.ng@ieee.org

Abstract —Heterogeneous Wireless Networks (HWNs), including several different wireless technologies, are recent solutions that provide seamless communication for mobile users. However, with the development of various wireless networks, the spectrum detection of cognitive networks and terminals becomes more complicated, which decreases the detection performance. The accuracy and efficiency of the spectrum detection will be reduced due to integrating various wireless networks with different characteristics into a diverse overlay system. In this paper, we design a high accuracy recognition algorithm for Cognitive Radio (CR) signal based on machine learning in HWNs, which can recognize the received signal type through extracting the features. This algorithm can recognize the signal types blindly with low complexity, and prevent the influence of “hostile terminals”. Simulation results indicate that the algorithm we proposed can achieve high recognition accuracy under either Additive White Gaussian Noise (AWGN) channel or Rayleigh fading channel.

Index Terms—Signal recognition, cognitive radio, machine learning, SVM, heterogeneous wireless networks

I. Introduction

In recent years, wireless communication technologies are developing so rapidly that there has been a spate of interest in the integration of various wireless networks which will provide mobile terminals with the seamless communication service. Heterogeneous wireless networks (HWNs) are considered as a promising way to cost-effectively enhance coverage and capacity of the network [1], especially in LTE network [2].

Cognitive Radio (CR) is provided as a virtual technology to increase the efficiency of spectrum effectively [3], [4]. CR terminals, which use the idle licensed spectrum for communication, can't cause interference between licenses users and adjacent communication users [5]. There are two major challenges for cognitive networks and terminals,

(i) The cognitive network and terminals sense the wireless environment and communicate through using the vacant spectrum. Thus, cognitive terminals require efficient spectrum detection techniques.

(ii) There will be more cognitive terminals to access the idle spectrum. But there are always some hostile terminals which violate or ignore the communication protocol. How to solve the "hostile terminal", which will influence the normal cognitive terminals to search and access idle spectrum, is a very important issue [6], [7].

Faced with these challenges, a reliable and high-efficiency spectrum detection method is necessary for the cognitive networks and terminals. A lot of works have already been done in spectrum detection and a lot of achievements have been realized [8]-[11]. The spectrum detection problems become more complicated due to the various network deployed in HWNs. The transmission rate and signal convergence range significantly affect the network performance [12]. As a result, many spectrum detection methods are unavailable or the detection results are not ideal in HWNs.

Cognitive signal recognition is a useful technique to solve this detection problem in cognitive radio under HWNs. It can prevent the influence of “hostile terminals” and then improve the spectrum's utilization [13], [14].

The identification of the cognitive signal does not need any prior information of received signals, and the cognitive signal recognition can be composed of two parts: decision theoretic approach and feature-based approach [15], [16]. In [17], the authors describe a discrete likelihood-ratio test based on rapid-estimation approach, aiming to identify the modulation solutions blindly for uninterrupted date demodulation in real time. Feature-based algorithms use signal features such as signal statistics, wavelet transform, signal constellation to distinguish the various modulation types and constellations [18]. In [19], the proposed algorithm is characterized by higher order statistical moments of wavelet transform; the classifier is a multi-layer neural network with resilient backpropagation learning algorithm. In [20], the feature parameters of received signal are extracted using HHT and singular values of matrix which is composed of instantaneous parameters are used as characteristic vector and inputted to the Generalized Regression Neural Network (GRNN) to recognize the modulation of the signal.

In this paper, we describe a high accuracy cognitive signal recognition algorithm based on machine learning which can distinguish different radio signal types in HWNs, and the priori information is not required in the

Manuscript received January 18, 2017; revised March 29, 2017.
This work was supported by National Major Project under Grant No. 2015ZX03001013-002.
Corresponding author email: wjbjekyll@163.com.
doi:10.12720/jcm.12.3.173-179

algorithm. There are two steps in the proposed algorithm: first, we extract the features by using the Daubechies5 wavelet transform and Fractional Fourier Transform (FRFT), and then we use a classifier based on machine learning to determine the signal types. Through the algorithm, we can get the modulation information of the received signals. The simulation results indicate that the algorithm can achieve good performance whether in AWGN channel or Rayleigh fading channel at acceptable SNR range.

The paper is organized as follows: Section 2 introduces system model briefly. Signal recognition algorithm design is provided in Section 3, which analyzes the process of feature extraction considering Daubechies5 wavelet transform and FRFT, and also focuses on the classification method based on machine learning. In Section 4, simulation results and performance analysis are presented. Finally, conclusions are drawn in Section 5.

II. System Model

A. Heterogeneous Wireless Networks

A wideband wireless system in HWNs is represented in Fig. 1. Cognitive terminals detect the whole broadband frequency spectrum and find the spectrum holes continuously. When spectrum holes appeared again, cognitive terminals can detect it immediately and make it accessible to communication.

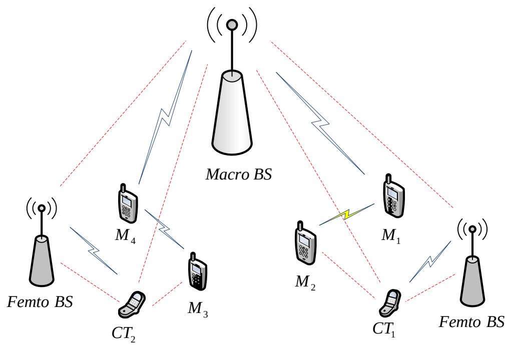


Fig. 1. A wideband wireless system in HWNs

As shown in Fig. 2, the transmit signal vectors of femto-BS and macro-BS are denoted as S_f and S_m, and the transmit signal vectors of cognitive terminal 2 (CT_2) and mobile 2 (M_2) are denoted as S_{c2}, S_{mob}. The H_{mc} is the channel matrix for macro-BS and cognitive terminal 1 (CT_1), H_{fc} is the channel matrix for femto-BS and CT_2, H_{cc} is the channel matrix for CT_2 and CT_1, and H_{mobc} is the channel matrix for macro-MS mobile 2 M_2 and CT_1 respectively. The received signal vectors at CT_1 can be represented as,

$$r_c = H_{mc}S_m + H_{fc}S_f + H_{cc}S_{c2} + H_{mobc}S_{mob} + n \tag{1}$$

The received signal vectors at macro-MS mobile 1 (M_1) can be written as,

$$r_m = H_{mc}S_m + H_{fm}S_f + n \tag{2}$$

where, in (1), (2), n represents the channel noise.

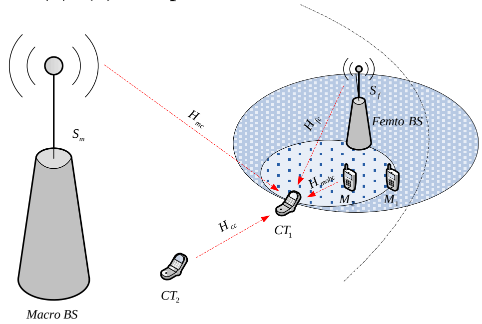


Fig. 2. Cognitive radio is in active

As can be seen in Fig. 2, assuming there is a working terminal which would violate or ignore the communication rules or allocated strategies and access spectrum randomly, it could obtain information from all the transmitted signals as sent by all the transmitters. So the spectrum holes may always be occupied by the hostile terminal. As a result, the terminal may result in waste of resources in the available and idle spectrum, and even destroy all the HWNs.

We can solve the problem through the following three steps,

(i) Recognize the signal types, which are occupying the wideband frequency.

(ii) Analyze the recognized signal types, and identify the hostile signals.

(iii) Avoid hostile signals with some effective strategy.

In this paper, we mainly research how to recognize the signal types.

We describe a low-complexity algorithm to recognize signal types in HWNs, after that, cognitive terminals can formulate a strategy to prevent the interference of hostile terminals.

B. Channel Model

The wireless channel model is composed of AWGN channel and Rayleigh fading channel. The average value of noise in the AWGN channel is 0, which adds to the transmitted signal after Rayleigh fading. The received signal at the terminals is written as,

$$y(\mathrm{t}) = A(\mathrm{t}) \cdot \mathrm{x}(\mathrm{t}) + \omega(\mathrm{t}) \tag{3}$$

where $y(\mathrm{t})$ is the received signal, $A(\mathrm{t})$ changes along with the channel, $\mathrm{x}(\mathrm{t})$ represents uncharted source signals received by the cognitive terminals, and $\omega(\mathrm{t})$ is AWGN with variance σ^2.

III. Proposed Signal Recognition Algorithm

Signal recognition has become a key topic for electronic surveillance in cognitive radio, and it plays a vital role in military and commercial filed [13]. In this paper, we proposed a high reliability and low complexity recognition algorithm using feature-based approach under HWNs. Fig. 3 shows the process of signal recognition, which consists of two blocks: feature extraction and classifier. In the feature extraction block, we use Daubechies5 wavelet transform and FRFT to obtain the signal feature. After that, we choose a classifier based on machine learning to recognize the signal type. Then, the recognized signal type can be used for further analysis.

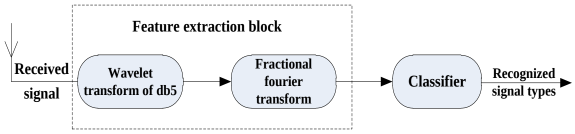


Fig. 3. The process of signal recognition

A. Feature Extraction

1) The necessary features

The key step of the signal recognition is to extract the features for identification. The features of most signals in time domain and frequency domain are not complex; hence they are applied in signal identification widely. In this paper, we choose five features that are as follows,

(i) Maximum of the spectral power density of the normalized centered instantaneous amplitude $\gamma_{\max}$

$$\gamma_{\max} = \frac{\max\left|FFT\left[a_{cn}(i)\right]\right|^2}{N_s} \tag{4}$$

$$a_{cn}(i) = a(i)/m_a - 1 \tag{5}$$

where N_s is the number of samples, $a_{cn}(i)$ is the normalized center instantaneous amplitude, m_a is the average of the amplitude. It is often used to differentiate the amplitude modulation signal.

(ii) Standard deviation of the normalized centered instantaneous amplitude σ_{aa}

$$\sigma_{aa} = \sqrt{\frac{1}{N_s}\left(\sum_{i=1}^{N_s} a_{cn}^2(i)\right) - \left(\frac{1}{N_s}\sum_{i=1}^{N_s}\left|a_{cn}(i)\right|\right)^2} \tag{6}$$

(iii) Standard deviation of the absolute nonlinear centered instantaneous phase σ_{ap}

$$\sigma_{ap} = \sqrt{\frac{1}{c}\left(\sum_{a_n(i)>a_t} \varphi_{NL}^2(i)\right) - \left(\frac{1}{c}\sum_{a_n(i)>a_t}\left|\varphi_{NL}(i)\right|\right)^2} \tag{7}$$

where a_t is the threshold used to remove weak signals, $\varphi_{NL}(i)$ is the value of the nonlinear component, c is the number of non-weak signal values. It can be used to distinguish the different phase modulation signal.

(iv) Standard deviation of the non-linear centered direct phase σ_{dp}

$$\sigma_{dp} = \sqrt{\frac{1}{c}\left(\sum_{a_n(i)>a_t} \varphi_{NL}^2(i)\right) - \left(\frac{1}{c}\sum_{a_n(i)>a_t}\varphi_{NL}(i)\right)^2} \tag{8}$$

(v) Standard deviation of the absolute non-linear instantaneous frequency σ_{af}

$$\sigma_{af} = \sqrt{\frac{1}{c}\left(\sum_{a_n(i)>a_t} f_N^2(i)\right) - \left(\frac{1}{c}\sum_{a_n(i)>a_t}\left|f_N(i)\right|\right)^2} \tag{9}$$

$$f_N(i) = \frac{f_m(i)}{R_s} = \frac{f(i) - m_f}{R_s} = \frac{f(i) - \frac{1}{N_s}\sum_{i=1}^{N_s} f(i)}{R_s} \tag{10}$$

where R_s is the symbol rate, $f(i)$ is the instantaneous frequency. It can be used to distinguish different frequency modulation signals

2) Wavelet transform

Wavelet transform can achieve better results for analysis of non-stationary signals. The wavelet basis is defined as

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \tag{11}$$

We use Daubechies5 as wavelet basis in this paper. The four filters associated with Daubechies5 wavelet is shown in Fig. 4. The effect of wavelet transform is to extract the abrupt feature of the received signal.

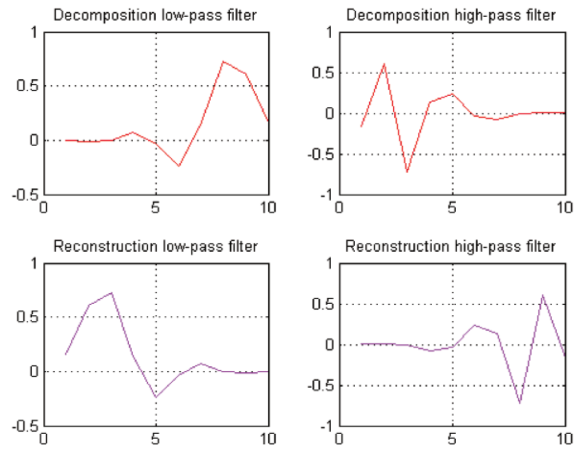


Fig. 4. The four filters associated with Daubechies5 wavelet

3) Fractional fourier transform

The FRFT offers a way to solve the problem of additional degree of freedom as parameter α is used in the particular signal processing [21].

For any real α, the α-angle FRFT of a function f can be denoted as,

$$\left(F_s^{\alpha} f\right)(x) = \sum_{m=0}^{+\infty} B_m \lambda_m(s;\alpha)\Phi_m(x) \tag{12}$$

$$f(x) = \sum_{m=0}^{+\infty} B_m \Phi_m(x) \tag{13}$$

$$B_m = \left\langle f, \varphi_m \right\rangle = \int_R f(x)\overline{\Phi_m}(x)\,dx, m = 0,1,2... \tag{14}$$

The process of feature extraction can be seen in Fig. 5. The feature obtained by wavelet transform is reflected by FRFT, which can show the time-frequency characteristic and the mutation characteristic of the original signal better.

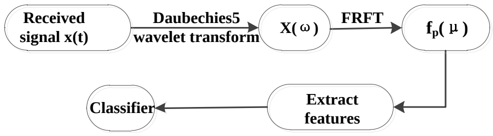


Fig. 5. Feature extraction process

B. Machine Learning Mechanism

1) Support vector machine

Support Vector Machine (SVM) is one of the most common machine learning, it is also the most practical part of statistical theory and it is based on structural risk minimization principle. Compared to the neural network classifier, it has many advantages in solving small sample, non-linear and high-dimensional pattern recognition, and it has stronger generalization ability.

The purpose of support vector machine is to find the optimal classification hyperplane for binary classification problem. Firstly, the input space is transformed into a high dimensional space by nonlinear transformation, and then the optimal linear hyperplane is obtained in the new space.

Suppose there are training data as follows,

$$(x_1,y_1),(x_2,y_2),\cdots,(x_n,y_n),x_i\in R^n,y_i\in\{+1,-1\} \quad (15)$$

where x_i is the input pattern set, y_i is +1 when x_i belongs to the first sort, otherwise y_i is -1 .These data can be completely separated from the hyperplane $(w\cdot x)+b=0$. The problem can be transformed into solving optimization.

$$\begin{aligned}&\min_{wb\xi}\frac{1}{2}\|w\|^2+C\left(\sum_{i=1}^{l}\xi_i\right)\\&s.t.\ y_i\left[(w\cdot x)+b\right]-1+\xi_i\geq 0,\xi_i\geq 0,i=1,2\cdots l\end{aligned} \quad (16)$$

where w is the coefficient vector, b is the threshold for classification, C is the penalty factor, ξ_i is the relaxation variable. We use the Lagrangian multiplier to solve the above quadratic programming problem and can obtain the decision function as follows,

$$f(x)=\mathrm{sgn}\left(\sum_{i=1}^{l}\alpha_i\, y_i K(x_i,x)+b\right) \quad (17)$$

where α_i is the Lagrangian multiplier, $K(x_i,x)$ represents the kernel function. The role of the kernel function is to map the nonlinear sample data to the high-dimensional space so as to achieve linear classification in the high-dimensional space. The common kernel functions include polynomial kernel function $K(x_i,x)=(x_i\cdot x+1)^d$, the Radial Basis Function (RBF) $K(x_i,x)=\exp\left(-\|x-x_i\|^2/\sigma^2\right)$, the sigmoid kernel function $K(x_i,x)=\tanh(k\cdot x_i\cdot x+\theta)$.

2) Classification using SVM

Support Vector Machine (SVM) is proposed for binary classification problems, while digital modulation signal recognition is a typical multi-class classification problem. Therefore, the above method should be improved so that support vector machine can be applied to multi-classification problem. In this paper, we adopt the following method to solve the multi-classification problem,

1. One Vs All

We consider one category of samples as a category and the remaining categories of samples as another category. The problem is still a binary classification of the problem.

2. One Vs One

We select two samples randomly to construct a t binary classifier from N samples, and $N(N-1)/2$ classification functions are constructed totally. The testing sample is classified by each classifier, and the category of the testing sample is decided by the method of voting. Although this method avoids the problem of data set inclination, but the number of classifiers increases, resulting in slow speed of training and decision.

3. Directed Acyclic Graph (DAG-SVM)

In order to solve the problem of misclassification and rejecting classification in the method of "One Vs One", Directed Acyclic Graph (DAG) is proposed by Plat, exported from Decision direct acyclic graph (DDAG). The difference between "One Vs One" and DAG-SVM is the organizational structure of the classifier showed in Fig. 6.

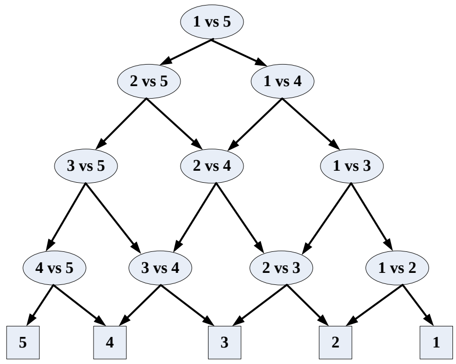


Fig. 6. The structure of DAG-SVM

In the proposed algorithm, we choose the RBF as the kernel function of SVM classifier. Compare to the polynomial kernel function, RBF has smaller number of parameters, which affects the complexity of the training model directly.

The classification process is showed in Fig. 7.

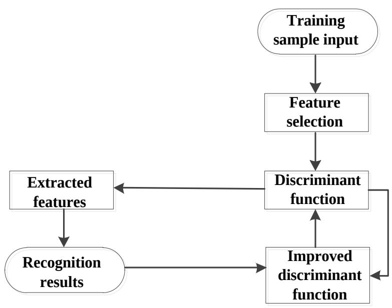


Fig. 7. The classification scheme

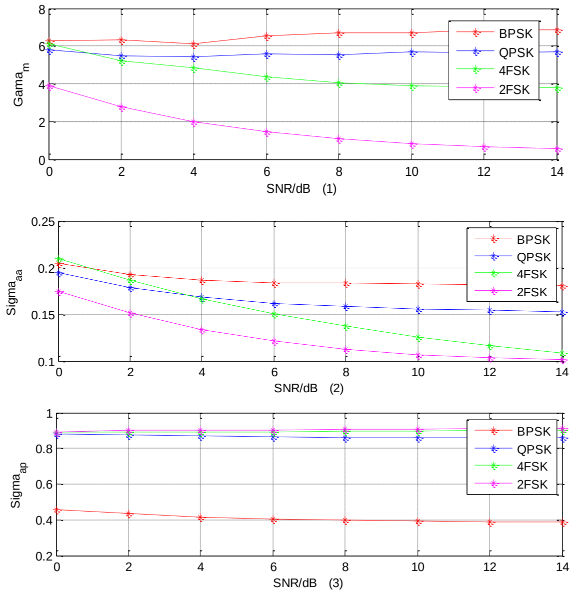
IV. Simulation Results and Performance Analysis

In this section, we perform extensive simulations and analysis to prove the efficacy of the proposed algorithm. Four conventional signal types (2FSK, 4FSK, BPSK and QPSK) are adopted for the recognition algorithm in MATLAB. The simulation results and performance analysis of the proposed algorithm can be divided into two parts: single type recognition performance in AWGN channel, single type recognition performance in Rayleigh fading channel. We set the following parameters: signal symbol rate (20Kb/s) and frequency of the carrier wave (100 KHz). 400 frames of data are generated in simulation, the Daubechies5 wavelet transforms and the FRFT are computed, applying statistical sampling points to extract the set of features. 100 samples are used to train the SVM model and the remaining 300 samples are used for testing.

A. Recognition Performance in AWGN Channel

Fig. 8 (1)-(5) shows the characters of $\gamma_{\max}$, σ_{aa}, σ_{ap}, σ_{dp} and σ_{af} in AWGN channel. It can be seen from the characteristic curve, the curve interval of the character $\gamma_{\max}$, σ_{aa} of QPSK, 2FSK is large, and the curve interval of the character σ_{ap}, σ_{dp}, σ_{af} of BPSK, 4FSK is large. It is easy to distinguish the signal type depending on the characters.

In Fig. 9, the fold lines indicate the single type recognition performance of the proposed algorithm in AWGN channel. The simulation shows that the correct recognition probability of BPSK in AWGN channel is almost 100% when the SNRs vary from 0dB to 14dB. When SNR=6dB, the recognition probabilities of the three signal types (2FSK, 4FSK, BPSK) are higher than 96%.



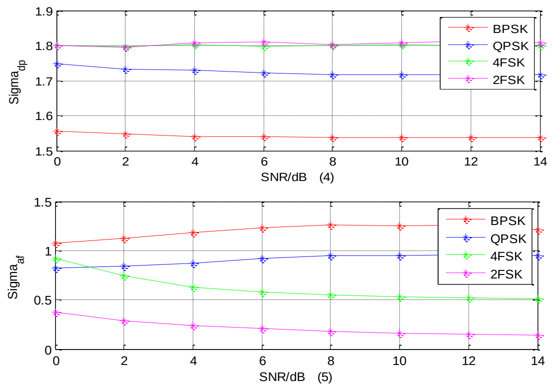


Fig. 8. The characters of signals in AWGN channel

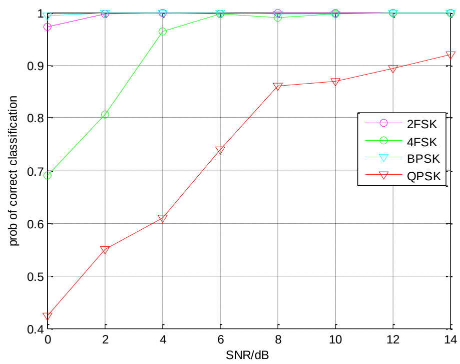
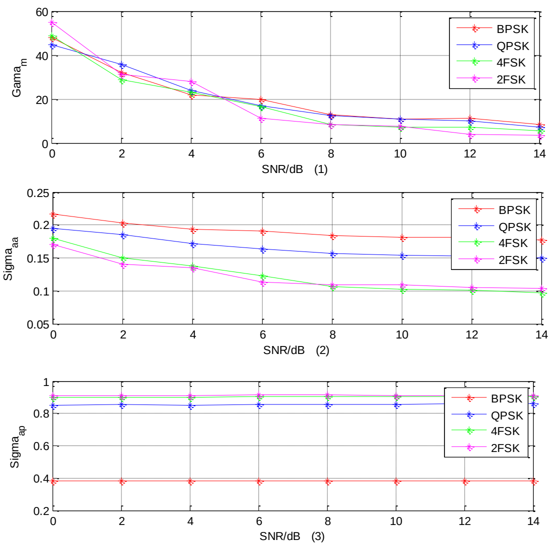


Fig. 9. The correct recognition probability in AWGN channel

B. Recognition Performance in Rayleigh Fading Channel

Fig. 10 (1)-(5) shows the characters of $\gamma_{\max}$, σ_{aa}, σ_{ap}, σ_{dp} and σ_{af} in Rayleigh fading channel. From the figure, we can find that the curve interval of the character σ_{aa}, σ_{ap} of BPSK, 4FSK is large, and the curve interval of the character σ_{dp}, σ_{af} of QPSK, 2FSK is large. It is easy to distinguish the signal type depending on the characters.



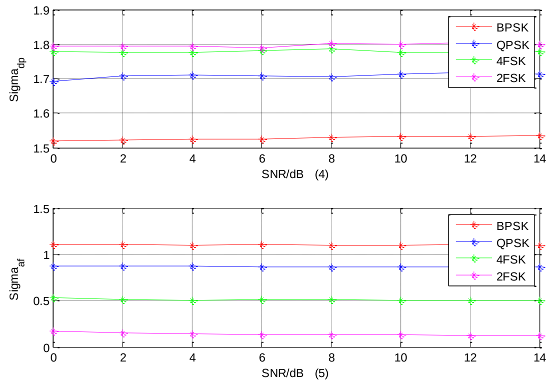


Fig. 10. The characters of signals in Rayleigh fading channel

In Fig. 11, the channel is Rayleigh fading channel. From the simulation results, with the increase of SNR, the probability of correct classification is on the rise. When SNR=8dB, the recognition probabilities of the four signal types (2FSK, 4FSK, BPSK, QPSK) are higher than 85%. The recognition performance in Rayleigh fading channel is a bit worse than that in AWGN, but is still satisfying.

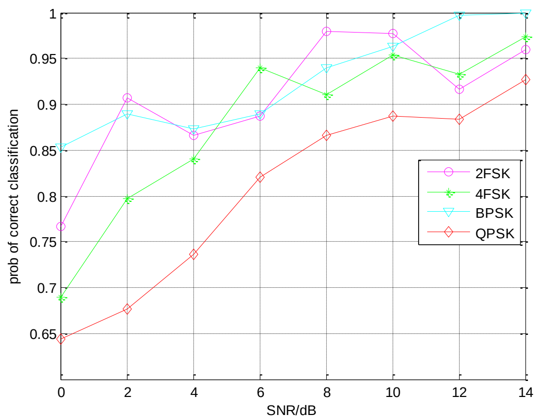


Fig. 11. The correct recognition probability in Rayleigh fading channel

V. Conclusions

In the paper, we propose a high reliable signal recognition algorithm of cognitive radio in heterogeneous wireless networks. Feature-based approach is used in this algorithm, which consists of Daubechies5 wavelet transform and FRFT, and can be applied to complex environment of HWNs. This algorithm can be realized with low complexity and distinguish different signal types. According to the signal type, HWNs can prevent the ``hostile terminals" influence. Here we simulate with four signal types (2FSK, 4FSK, BPSK and QPSK).

Based on the simulation results, we can conclude that the proposed algorithm shows superior performance in terms of low complexity, high recognition rate and efficiency under the AWGN and Rayleigh fading channels respectively, as compared to traditional schemes. What's more, the recognition performance in AWGN channel is a bit better than that in Rayleigh fading channel.

References

[1] A. Gorcin and H. Arslan, "Signal identification for adaptive spectrum hyperspace access in wireless communications systems," *IEEE Wireless Communications*, vol. 52, no. 10, pp. 134-145, 2014.

[2] A. Damnjanovic, *et al.*, "A survey on 3GPP heterogeneous networks," *IEEE Wireless Communications*, vol. 18, no. 3, pp. 10-21, 2011.

[3] T. K. Kim, H. M. Kim, M. G. Song, and G. H. Im, "Improved spectrum-sharing protocol for cognitive radio networks with multiuser cooperation," *IEEE Personal Communications*, 2015.

[4] A. Hess, F. Malandrino, N. J. Kaminski, T. K. Wijaya, and L. A. DaSilva, "Cognitive radio algorithms coexisting in a network: Performance and parameter sensitivity," *IEEE Transactions on Cognitive Communications and Networking*, vol. 2, no. 4, pp. 381-396, 2016.

[5] H. E. Egilmez and A. Ortega, "Wavelet-based compressed spectrum sensing for cognitive radio wireless networks," in *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing*, 2015, pp. 3157-3161.

[6] G. Sklivanitis, A. Gannon, S. N. Batalama, and D. A. Pados, "Addressing next-generation wireless challenges with commercial software-defined radio platforms," *IEEE Communications Magazine*, vol. 54, no. 1, pp. 59-67, 2016.

[7] Z. Guan, *et al.*, "Distributed resource management for cognitive ad hoc networks with cooperative relays," *IEEE/ACM Transactions on Networking*, vol. 24, no. 3, pp. 1675-1689, 2016.

[8] J. So and W. Sung, "Group-Based multibit cooperative spectrum sensing for cognitive radio networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 12, pp. 10193-10198, 2016.

[9] Z. Dai, J. Liu, C. Wang, and K. Long, "An adaptive cooperation communication strategy for enhanced opportunistic spectrum access in cognitive radios," *IEEE Communications Letters*, vol. 16, no. 1, pp. 40-43, 2012.

[10] S. Lv and J. Liu, "A novel signal separation algorithm based on compressed sensing for wideband spectrum sensing in cognitive radio networks," *International Journal of Communication Systems*, vol. 1, no. 7, pp. 4432-4436, 2013.

[11] Z. Guan, *et al.*, "On the effect of cooperative relaying on the performance of video streaming applications in cognitive radio networks," in *Proc. IEEE International Conference on Communications*, 2011.

[12] W. H. Yang, Y. C. Wang, Y. C. Tseng, and B. S. Lin, "Energy-efficient network selection with mobility pattern awareness in an integrated WiMAX and WiFi network," *International Journal of Communication Systems*, vol. 23, no. 2, pp. 213-230, 2010.

[13] D. Liu, C. Li, J. Liu, and K. Long, "A novel signal separation algorithm for wideband spectrum sensing in cognitive networks," in *Proc. IEEE Global Communications Conference*, 2010, pp. 1-6.

[14] Z. Guan, T. Melodia, and G. Scutari, "To transmit or not to transmit? Distributed queueing games in

infrastructureless wireless networks," *IEEE/ACM Transactions on Networking*, vol. 24, no. 2, pp. 1153-1166, 2016.

[15] N. Madhavan, A. P. Vinod, A. S. Madhukumar, and A. K. Krishna, "Spectrum sensing and modulation classification for cognitive radios using cumulants based on fractional lower order statistics," *AEU-International Journal of Electronics and Communications*, vol. 67, pp. 479-490, 2013.

[16] P. Panagiotou, A. Anastastasoupoulos, and A. Polydoros, "Likelihood ratio tests for modulation classification," in *Proc. IEEE Military Communications Conference*, 2000, pp. 670-674.

[17] J. L. Xu, W. Su, and M. Zhou, "Software-defined radio equipped with rapid modulation recognition," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 4, pp. 1659-1667, 2010.

[18] B. Ramkumar, "Automatic modulation classification for cognitive radios using cyclic feature detection," *IEEE Circuits and Systems Magazine*, vol. 9, no. 2, pp. 27-45, 2009.

[19] K. Hassan, *et al.*, "Automatic modulation recognition using wavelet transform and neural network," in *Proc. IEEE 9th International Conference on Intelligent Transport Systems Telecommunications*, 2009.

[20] Y. Hou and H. Tian, "An automatic modulation recognition algorithm based on HHT and SVD," in *Proc. IEEE 3rd International Congress on Image and Signal Processing*, 2010.

[21] J. Liu and Q. Luo, "A novel modulation classification algorithm based on Daubechies5 wavelet and fractional fourier transform in cognitive radio," in *Proc. IEEE 14th International Conference on Communication Technology*, 2012, pp. 115-120.

Jian Liu received his B.S. degree in Automatic Control Theory and Applications from Shandong University, China, in 2000, and the Ph.D. degree in School of Information Science and Engineering from Shandong University in 2008. He is currently an associate professor of University of Science and Technology (USTB), Beijing, China. His research interests include cognitive radio networks, mobile mesh networks, and LTE-A. He is an IEEE member since 2009.

Jibin Wang received his Bachelor degree in Communication Engineering from University of Science and Technology Beijing (USTB), Beijing, China, in 2013. He is currently studying for a master's degree at University of Science and Technology Beijing (USTB), Beijing, China. His research interests include cognitive radio networks and modulation identification.

Sani Umar Abdullahi received his B.Eng. degree in Electrical Engineering from Ahmadu Bello University Zaria, Nigeria in 2008 and an M.S. degree in Mobile and Satellite Communications from the Centre for Communications and Systems Research (CCSR) of University of Surrey in 2009. He is currently pursuing a Ph.D. degree with the School of Communications and Computer Engineering, University of Science and Technology (USTB), Beijing, China. His research interests include resource allocation and interference management in heterogeneous networks, cognitive radio, and use of stochastic geometry in mobile wireless networks.