Spectrum Sensing Algorithm Based on Random Forest in Dynamic Fading Channel

39

Zhijun Gao and Xin Wang

Abstract Efficient utilization and energy saving of spectrum is a crucial technology in 5G, and spectrum sensing is an important foundation and core of efficient utilization of spectrum resources. At present, good results have been achieved for spectrum sensing in Gaussian channels, but in dynamic fading channels, due to fading and multi-path transmission factors, the spectrum sensing performance is poor. To solve this problem, this paper first proposes a perceptive system model under dynamic fading channel, and on the basis of this model, a spectral sensing algorithm based on the random forest is proposed. The algorithm extracts the fading amplitude gain, the energy value of the received signal, and the characteristic parameters of the signal cycle spectrum in the scene of the dynamic fading channel as the sample parameters to construct the random forest and then senses and classifies the constructed random forest signals to determine the state of the channel occupancy.

Keywords 5G · Spectrum sensing · Dynamic fading channel · Random forest

1 Introduction

5G is a new generation of the mobile communication system for the development needs after 2020, which has received extensive attention and research from enterprises, research institutes, and universities around the world. Considering that the current shortage of spectrum resources makes the development of wireless communication seriously restricted, how to efficiently use the limited spectrum resources is an urgent problem to be solved in 5G research [\[1\]](#page-7-0). Spectrum sensing provides an important basis for solving this problem and is a new technology that is expected to alleviate the problem of spectrum resource depletion and low utilization. Currently, spectrum sensing technology can be divided into three methods: Energy Detection (ED), Matched Filter Detection (MFD), and Cyclostationary Detection (CD) [\[2\]](#page-7-1). The energy detection method is simple and easy to operate, and the computational

Z. Gao \cdot X. Wang (\boxtimes)

Faculty of Information and Control Engineering, Shenyang Jianzhu University, Shenyang, China e-mail: wangx7988@sjzu.edu.cn

[©] The Author(s), under exclusive license to Springer Nature Singapore Pte Ltd. 2021 Y. Li et al. (eds.), *Advances in Simulation and Process Modelling*,

Advances in Intelligent Systems and Computing 1305, https://doi.org/10.1007/978-981-33-4575-1_5

complexity is low, so it has been applied in many kinds of research. Unfortunately, the performance of energy detection is poor under low SNR [\[3\]](#page-7-2). Cyclic stationary feature detection can distinguish the non-coherent stationary noise signal energy from the received signal, and it has good robustness and noise resistance to the detection of unknown noise variables, so it can be applied to spectrum sensing problems in various noise environments. However, this algorithm has a high computational complexity [\[4\]](#page-7-3). The matched filter detection method can achieve higher processing gain and shorter detection time. However, this method needs to obtain the prior information of the primary user signal in advance. If the information is not accurate enough, then the performance of matching filter detection will be greatly affected. Besides, there must be an independent matching filter for each primary user receiver [\[5\]](#page-7-4).

In recent years, many researchers have studied spectral sensing methods and achieved good results. In [\[6\]](#page-7-5), Ahmed et al. proposed a GUESS algorithm with low complexity and communication overhead to realize efficient collaboration between sub-users and reduce the impact of network changes on perceived results. In [\[7\]](#page-7-6), Ganesan et al. proposed a distributed collaboration spectrum sensing strategy based on the distance between secondary users and primary users and matched each secondary user based on the distance between secondary users and primary users, thus improving the overall perception performance.With the development of machine learning, scholars have begun to use machine learning methods to solve the problem of spectrum perception. In [\[8\]](#page-7-7), a feature-based automatic modulation type classification algorithm is proposed by using the high-order cumulant as the recognition feature. These results improve the spectral sensing performance of Gaussian channels with high SNR to some extent. But in dynamic fading channels, the spectral sensing performance is poor due to fading and multi-path transmission factors.

In order to solve the above problems, this paper proposes a spectrum sensing algorithm based on random forest in dynamic fading channel. The contributions of this paper are as follows:

- A sensing system model in dynamic fading channel is proposed. For any channel, whether the channel state is idle or not can be reduced to a binary hypothesis testing model;
- In the dynamic fading channel, the fading amplitude gain a_k , the received signal energy value y_n , the mathematical expectation, and variance of the signal cyclic spectrum characteristics are extracted as the sample parameters to construct the random forest; and
- The constructed random forest signals are perceived and classified to determine the channel occupancy state.

The remainder of the paper is organized as follows. In Sect. [2,](#page-2-0) system model is described. The proposed algorithm is investigated in Sect. [3](#page-3-0) and is well validated with simulation in Sect. [4.](#page-5-0) The concluding remarks are made in Sect. [5.](#page-7-8)

2 System Model

2.1 Primary User Status Model

For secondary users, their perception of whether the channel is occupied, that is, whether there are primary users in the channel, can be summarized as a binary hypothesis testing model.

$$
\begin{cases}\nH_0: y(t) = n(t) \\
H_1: y(t) = s(t) + n(t)\n\end{cases} (1)
$$

Under this model, the main user energy and can be expressed by the following formula.

$$
E_{y} = \begin{cases} \sum_{i=1}^{M} n_{i}^{2}, & H_{0} \\ \sum_{i=1}^{M} (a_{i}x_{i} + n_{i})^{2}, & H_{1} \end{cases}
$$
 (2)

where *M* represents the number of sampling points in T_s ; channel noise *n* is the Additive White Gaussian Noise (AWGN), which means that value is 0, and variance is σ^2 . *H*₀ and *H*₁ correspond to the presence and absence of primary user signals in the detected frequency band, respectively.

The main goal of spectrum sensing is to judge hypothesis testing by receiving signals and finally determine whether there is a primary user signal in the current detection cycle. The traditional ED spectrum sensing method sets the threshold according to certain criteria and compares the received signal energy with the threshold value to obtain the decision result. However, in time-varying fading channels, the variation of channel gain with time will undoubtedly greatly increase the difficulty of threshold determination, thus significantly reducing the spectrum sensing performance in practical applications. In view of this, this paper not only takes the received signal energy as the sensing parameter, but also introduces other sensing parameters to obtain more accurate results.

2.2 Dynamic Fading Channel Awareness System Model

In this paper, it is assumed that time-varying fading channels are subject to Rayleigh time-slowing fading characteristics; that is, the probability distribution of random channel gain is Rayleigh distribution.

$$
f(a) = \frac{a}{\sigma_R^2} \exp\left(-\frac{a}{2\sigma_R^2}\right), a \in [0, \infty)
$$
 (3)

where *a* represents channel gain, and σ^2 represents variance of Rayleigh distribution. The channel gain is divided into *K* discrete states ($K \geq 3$). If $[v_K, v_{k+1}]$ is used to represent the boundary value of the *K*-th discrete state channel gain, then the channel gain corresponding to that state can be defined as follows.

$$
a_k = \frac{\int_{v_k}^{v_{k+1}} af(a)da}{\int_{v_k}^{v_{k+1}} f(a)da}, \ k = 0, \dots, K - 1
$$
 (4)

According to the main user's working state model and the main user's energy and expression, the dynamic fading channel awareness system model proposed can be expressed as

$$
\begin{cases}\nS_i = f(s_i) \\
a_k = h(a), \quad n = 0, ..., N - 1 \\
y_n = g(a, s_i, n_i)\n\end{cases}
$$
\n(5)

where S_i represents the state of the primary user at time i , and the migration is carried out according to the specific state function $F(\cdot)$. s_i represents the signal transmitted by the primary user at time *i*, when the primary user signal does not exist, that is, when the authorized frequency band is free, $S_i = 0$; when there is a primary user signal, $S_i = 1$. a_k represents the amplitude gain of fading channel at time K, which is updated according to the specific state transfer function $H(\cdot)$. For cognitive users, their perceived signal y_n is the energy sum of the sampled signal in a specific observation time window, as shown in Eq. [\(2\)](#page-2-1). When there is no primary user signal, the perception signal y_n obeys the center chi-square distribution with M degree of freedom, $y_n \sim \chi^2_M$; when there is the perception signal y_n obeys the non-center chisquare distribution with *M* degree of freedom, $y_n \sim \chi^2_M(K)$, its non-center parameter $K = M(a_k x_k)^2$.

3 The Proposed Algorithm

Based on the perceptive system model of dynamic fading channel in Sect. [2.2,](#page-2-2) a spectrum sensing algorithm based on random forest is proposed. The algorithm extracts fading amplitude gain, energy value of received signal, and characteristic parameters of signal cycle spectrum in the scene of dynamic fading channel as sample parameters for constructing random forest and perceiving and classifying the constructed random forest signals.

If the received signal has multiple cycle frequencies, then the cycle spectrum with the maximum energy is taken as $S(k)$. $S(k)$ obeys the Gaussian distribution.

$$
\begin{cases}\nH_0: S(k) \sim N(0, \sigma_0^2) \\
H_1: S(k) \sim N(\mu, \sigma_0^2 + \sigma_s^2 + \sigma_{sn}^2)\n\end{cases} (6)
$$

Cyclic spectrum characteristics can be characterized by mean and variance of Gaussian distribution; that is, when there is no main user signal, the mean value of characteristic parameters corresponding to $S(k)$ is 0, and the variance is σ_0^2 . When there is a primary user, the mean value of characteristic parameters corresponding to *S*(*k*) is μ , and the variance is $\sigma_0^2 + \sigma_s^2 + \sigma_{sn}^2$.

According to the above system model and the analysis of cyclic spectrum parameters, the amplitude gain of fading channel a_k , the energy of perceptive signal y_n , and the mean and variance of Gaussian distribution that can reflect the characteristics of cyclic spectrum are obtained as sample parameters. When the primary user does not exist, the corresponding eigenvector is $x_0 = (a_{k0}, y_{n0}, 0, \sigma_0^2)$. Otherwise, the corresponding eigenvector is $x_1 = (a_{k1}, y_{n1}, \mu, \sigma_0^2 + \sigma_s^2 + \sigma_m^2)$.

3.1 Random Forest Algorithm

Samples are generated according to the eigenvectors of the presence and nonpresence of the main user, and the sample set *G* is formed. Using the samples in *G*, the random forest is constructed, and the details of the random forest algorithm are described as following.

Random forest by Leo Breiman (2001) proposed a classification algorithm, which uses bootstrap resampling technology to repeatedly randomly extract N samples from the original training sample set N to generate a new training sample set training decision tree, and then generate M decision trees to form a random forest according to the above steps. The classification ability of a single tree may be very small, but after a large number of decision trees are randomly generated, a test sample can select the most likely classification through the classification results of each tree. The process of random forest is as follows:

1) N samples were selected from random samples;

2) K features are randomly selected from all the features, and a decision tree is built based on these features for the selected samples;

3) Repeat the above two steps m times to generate m decision trees and form a random forest;

4) For new data, after each tree decision, the final vote to confirm which category.

3.2 Dynamic Fading Channel Sensing Algorithm Based on Random Forest

According to the construction process of the random forest in algorithm 1, the constructed random forest is used to realize the perception of the occupying state of the primary user signal to the channel.

Dynamic fading channel sensing algorithm based on random forest called DFCS-RF is proposed in this section

The fading amplitude gain, energy value of received signal and characteristic parameters of signal cycle spectrum are extracted in the H_0 and H_1 respectively. According to these parameters, positive and negative samples are generated, in which positive samples correspond to the channel state in H_1 and negative samples correspond to the channel state in H_0 . Then, according to the process of the random forest, the random forest is constructed and used to classify and detect the samples.

4 Simulation Results

In this section, simulation results of detection performance of spectrum sensing method in Rayleigh fading channel are given.We first conduct simulations to compare the performance of detection probability (P_d) under our DFCS-RF algorithm with two classic algorithms, sensing algorithm based on Support Vector Machine (SVM) and Artificial Neural Network (ANN). BPSK and OFDM are used as primary user signals. ANN adopts BP neural network with two input nodes, ten hidden layer nodes, and two output nodes. SVM classifier adopts cross-validation method, $C = 50$, $\sigma = 0.875$. The number of random forest decision trees is $K = 100$.

It is shown, in Fig. [1,](#page-6-0) that the comparison of detection rates of the proposed algorithm, ANN algorithm and SVM algorithm for BPSK signal under different SNR environments. As can be seen from the figure, when the SNR is −15 dB, the detection rate of the proposed DFCS-RF algorithm is 0.87, and that of the ANN and SVM algorithms is 0.58 and 0.69, respectively. The detection rate of DFCS-RF algorithm is 29% higher than that of ANN algorithm and 18% higher than that of SVM algorithm. When SNR is −20 dB, the detection rate of DFCS-RF algorithm, ANN algorithm, and SVM algorithm is 0.73, 0.31 and 0.43, respectively. Compared with ANN algorithm and SVM algorithm, the detection rate of DFCS-RF algorithm is improved by 42% and 30%, respectively.

Figure [2](#page-6-1) shows that when OFDM signals appear, the detection rate of each algorithm is analyzed, and the detection rate of the proposed DFCS-RF algorithm decreases from 0.96 to 0.73 with the decrease of SNR. The detection rate of ANN algorithm decreased from 0.85 to 0.36. The detection rate of SVM algorithm decreased from 0.89 to 0.50. The detection rate of the proposed algorithm is significantly higher than that of the comparison algorithm.

The above results show that the proposed DFCS—RF algorithm has good detection performance, the algorithm can effectively extract the characterization of primary user signal characteristics of four parameters as sample parameter, and by using the random forest factors such as noise has the very good tolerance, not easily seen fitting phenomenon, etc., and thus effectively to achieve the dynamic spectrum sensing under the fading channel.

Fig. 1 Probability of detection of the proposed algorithm versus ANN, SVM, and DFCS-RF algorithms for BPSK

Fig. 2 Probability of detection of the proposed algorithm versus ANN, SVM, and DFCS-RF algorithms for OFDM

5 Conclusions

Spectrum energy saving is a crucial issue in 5G development. Based on spectrum energy saving, this paper proposes a random forest-based spectrum sensing algorithm for spectrum sensing under the scenario of dynamic fading channel. Based on the sensing system model of the dynamic fading channel, fading amplitude gain, energy value of received signals, and characteristic parameters of signal cycle spectrum in dynamic fading channel scenes are extracted as sample parameters for constructing random forest in the algorithm and perceived and classified by the constructed random forest. Simulation results show that the proposed DFCS-RF algorithm in the dynamic fading channel has good perceptive performance.

Acknowledgements This work was supported by the National key R and D plan tasks under contract 2018YFF0300304-04, National Natural Science Foundation of China under contract 61903357, Scientific research project of Liaoning Provincial Department of Education under contract LNJC201912, Liaoning Provincial Natural Science Foundation of China under contract 2020-MS-032 and China Postdoctoral Science Foundation under contract 2020M672600.

References

- 1. Gupta, A., Jha, R.K.: A survey of 5G network: architecture and emerging technologies. IEEE Access **3**, 1206–1232 (2015)
- 2. Choo, K.R., Gritzalis, S., Park, J.H.: Cryptographic solutions for industrial Internet-of-Things: research challenges and opportunities. IEEE Trans. Ind. Inform **14**(8), 3567–3569 (2018)
- 3. Liu, X., Jia, M., Zhang, X., Lu, W.: A novel multi-channel Internet of Things based on dynamic spectrum sharing in 5G communication. IEEE Internet Things J. **6**(4), 5962–5970 (2019)
- 4. Sahoo, P.K., Mohapatra, S., Sheu, J.: Dynamic spectrum allocation algorithms for industrial cognitive radio networks. IEEE Trans. Ind. Inform **14**(7), 3031–3043 (2018)
- 5. Zhang, K., Ni, J., Yang, K., Liang, X., Ren, J., Shen, X.S.: Security and privacy in smart city applications: challenges and solutions. IEEE Commun. Mag. **55**(1), 122–129 (2017)
- 6. Ahmed, N., Hadaller, D., Keshav, S.: GUESS: gossiping updates for efficient spectrum sensing. In: ACM2006, pp. 12–17. International Workshop on Decentralized Resource Sharing in Mobile Computing and Networking. USA, Los Angeles, USA (2006)
- 7. Ganesan, G. and Li, Y.: Cooperative spectrum sensing in cognitive radio networks. In: Proceedings of IEEE-DySPAN, 2005, pp. 137–143. Baltimore, USA (2005)
- 8. Liao, Y.,Wang, T., Song, L., Han, Z.: Listen-and-talk: protocol design and analysis for full-duplex cognitive radio networks. IEEE Trans. Veh. Technol. **66**(1), 656–667 (2017)