A spectrum sensing algorithm based on adaptive regional model

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ABSTRACT

Spectrum sensing in cognitive radio is a key technology to improve spectrum utilization. However, the current spectrum sensing algorithms have limited accuracy and are not flexible enough in complex communication environment. In this paper, a spectrum sensing algorithm based on adaptive regional model is proposed. The spatial information of the regional model is used to improve the performance of spectrum sensing. Through the adaptive adjustment, the cognitive nodes at different distances in the regional model ensures the sensing performance of the whole region. Results show that the regional model can improve the spectrum efficiency and deal with the complex environment of multi primary user base stations. The spectrum utilization of single region model is improved by 9% and the average difference between actual model accuracy and prediction accuracy is 0.48%. Through this regional model, a spectrum sensing algorithm with adaptive adjustment and high frequency spectrum utilization is realized.

Keywords: Spectrum sensing, regional model, adaptive adjustment

1. INTRODUCTION

Nowadays, the scarcity of spectrum resources is one of the major challenges in communication service development. Cognitive radio networks have been widely regarded as an effective approach to mitigate the inefficiency of spectrum utilization.

In the definition of cognitive radio, users are divided into secondary users and primary users. Secondary users can dynamically access the frequency band without affecting the primary users[1]. As the first step of cognitive radio, spectrum sensing technology aims to quickly and accurately judge whether the frequency band is idle[2].

In order to further improve the performance of spectrum sensing, cooperative sensing is proposed[3-4]. Traditional cooperative sensing can be divided into soft-cooperation and hard-cooperation. Both classification methods cannot take into account the detection probability and false alarm probability at the same time, and are vulnerable to changes of the channel. The trust-based cooperative spectrum sensing data fusion scheme was proposed by Wang et al. It not only improves the perception probability, but also considers the impact of malicious attacks to ensure the security of the system[5]. Zheng et al. proposed the CoMAC-based cooperative spectrum sensing (CSS) scheme to determine the presence of primary users, the simulation results show that this scheme can effectively improve the spectrum sensing probability, and is not affected by the channel occupancy probability[6].

Cognitive database is often used as an auxiliary technology in a cognitive radio system[7]. The cognitive database makes the regional model with cognitive function possible. The cognitive nodes in the regional model can make full use of geographic information to select appropriate sensing behavior, and achieve multi-dimensional spectrum sensing combined with the time-frequency information in the channel. Rahul Tandra et al.[8] proposed the concept of black, gray and white region and Wei et al.[9] further improve the spectrum efficiency of the regional model. Moreover, using the regional model, we can obtain a more accurate signal-to-noise ratio range. When using the machine learning model for spectrum sensing, we can train the sensing model with a more accurate training set to improve the accuracy of spectrum sensing.

In this paper, support vector machine (SVM) combined with adaptive region model is used for spectrum sensing, which improves the sensing performance and system throughput. The rest of this paper is organized as follows: Section 2 shows the system model. Section 3 shows the proposed algorithm. The simulation is presented in Section 4. Finally, Section 5 concludes the whole work.

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2. PROPOSED ALGORITHM

2.1 Construction of regional model

Let us begin with a simple regional model with cognitive radio network as shown in Figure 1, which has one primary base station and uniformly distributed cognitive base stations.

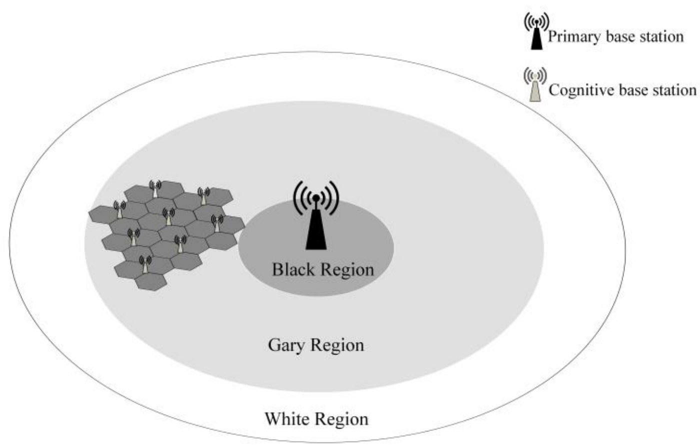

Figure 1. The regional model.

According to the user distribution and perceived behavior, the target is divided into black region, gray region and white region: 1. Black region: The region where the primary users are distributed, spectrum sensing can be carried out in low occupancy period. 2. Gray region: The region mainly for spectrum sensing. 3. White region: The region where cognitive users can freely access the frequency band. By dividing the regions with different sensing behaviors by distance, spectrum efficiency is improved and interference to primary users is reduced. For cognitive base stations, the primary user frequency band can also be divided into black, gray and white band.

The channel loss model in this paper is further simplified as:

$$L_P = A + \varepsilon \lg d \tag{1}$$

A is the fixed loss and ε is the path loss factor.

In the region model, the boundary of the black region is predetermined, the boundary of the gray region is determined by the cognitive base station interference in the white region, which needs to be lower than the interference threshold of primary users at the edge of the black region.

Firstly, the interference threshold at the edge of the black region needs to be calculated. Suppose that the transmission power of the primary base station is P_{S1}/(dBm), and the demodulation threshold of the primary users is τ/(dB). If the black area boundary is R_1/(km), the interference threshold I_0/(W) of the primary users is:

$$I_0 = 10^{\left(\frac{p_{s1} - A - \varepsilon \lg R_1 - \tau}{10} - 3\right)} \tag{2}$$

If the noise interference is I_n, the total interference I_c of cognitive base stations needs to ensure that $I_c \le I_0 - I_n$. Secondly, the range of white region can be calculated according to the interference threshold. Suppose P_{s2}/(W) is the transmission power of cognitive base station, the radius of gray region is R_2/(km), the radius of white region is R_3/(km), the distance between cognitive base station and primary user base station is l/(km), and the angle between the cognitive base station and the primary user is θ, the interference I/(W) of a single cognitive base station in the white area is:

$$I(l,\theta) = \frac{P_{S2}}{10^{A/10}(l^2 + R_1 - 2R_1 l \cos\theta)^{\varepsilon/2}} \tag{3}$$

Total interference I_c/(W) of all cognitive base stations is:

$$I_c = n\int_{R_2}^{R_3}\int_0^{2\pi} I(l,\theta) f_l(l) f_\theta(\theta) d\theta dl \tag{4}$$

$$n = \lambda\pi(R_3^2 - R_2^2) \tag{5}$$

$$f_l(l) = \frac{2l}{R_3^2 - R_2^2} \tag{6}$$

$$f_\theta(\theta) = \frac{1}{2\pi} \tag{7}$$

where n is the number of cognitive base stations, and λ is the distribution density of cognitive base stations in the white region.

It is difficult to obtain R_2 directly by equation (4). In this paper, the cumulative interference method is used to calculate the boundary as shown in Figure 2: let $R_2 = R_3 - a$, a is the step size, calculate the interference through double integral (4) by Simpson method[10], and compare it with the interference threshold. If the conditions are not met, reduce it successively in steps of a/km until it is lower than the interference threshold to obtain R_2.

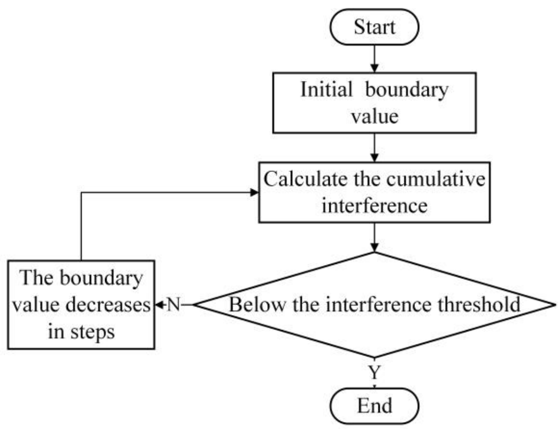

Figure 2. Flow chart for calculating the boundary of gray region.

In a complex environment, there are multiple primary user base stations and multiple frequency bands. The following cases may arise: 1. The black region of the primary base station may also be the gray region or white region of other primary base stations in different frequency bands. 2. The white region of the primary may also be the black or gray region of other primary base stations in the same frequency band. In order to solve the problem of frequency band selection, the concept of frequency band matrix is proposed in this paper.

Suppose there are N primary base stations $S_1, \dots S_N$, M frequency bands $B_1, \dots B_M$, and the black, gray and white region are marked as 1, 2 and 3 respectively, the frequency band matrix is shown in Table 1. If the frequency band has label 1, it is determined as black frequency band, if tag 1 does not exist, as long as tag 2 exists, it is determined as gray frequency band, if all labels are 3, it is determined as white band. Through this region construction method, not only the spectrum utilization can be further improved, but also the interference to the primary user can be avoided.

Table 1. The frequency band matrix.

	S_1	S_2	…	S_N	**Label of band**
B_1	1	2	…	3	1
B_2	2	2	…	3	2
…	…	…	…	…	…
B_M	3	3	…	3	3

2.2 Adaptability of regional model

In the actual communication environment, the signal strength received by base stations in different locations is different. How to ensure the consistency of sensing performance of a whole region is an urgent issue that need to be addressed. In this paper, the cognitive base station adopts the sampling frequency selection algorithm to ensure the stability and consistency of the overall regional sensing performance.

In the process of spectrum sensing, cognitive base stations have to consider two aspects: accuracy and real-time. The spectrum sensing problem can be simplified as a binary classification problem. In order to ensure the accuracy of the classification model, more eigenvalues are often required. In order to consider the real-time performance, the computational complexity of eigenvalues can not be too high. With the advantages of low computational complexity and easy acquisition, the sum of signal energy is often used as an important eigenvalue of spectrum sensing. Propose the noise signal be a Gaussian signal with mean value of 0 and variance of P_n, and the number of sampling points be n, suppose the received mixed signal is $x(t) = x_n(t) + x_r(t)$, $x_n(t)$ is the noise signal, $x_r(t)$ is the received signal, then the energy value of the mixed signal is:

$$Power = \sum_{k=0}^{n} x_n^2(k) + \sum_{k=0}^{n} x_r^2(k) + \sum_{k=0}^{n} x_n(k) x_r(k) \tag{8}$$

Because the signal $x_r(t)$ has periodicity, when n is large enough, $\sum_{k=0}^{n} x_n(k)x_r(k)$ can be regarded as 0, the chi-square distribution can be approximately normal distribution. If the received signal power is P_s, the sum of the received signal energy is nP_s, and the distribution function of the sum of the noise signal energy is:

$$f(x) = \frac{1}{2P_n\sqrt{n\pi}} e^{\frac{-(x-np_n)^2}{4np_n^2}} \tag{9}$$

According to the equation (9), noise energy obeys the standard normal distribution, so the probability that the noise signal energy is combined in a specific floating interval can be obtained. Let n_α be the α-quantile of the noise energy distribution, the probability of noise energy distribution in $(nP_n - \sqrt{2}nP_n n_\alpha, nPn + \sqrt{2}nP_n n_\alpha)$ is $2\alpha - 1$, and the fluctuation range of noise energy is $2\sqrt{2}nP_n n_\alpha$. According to the received signal energy combined with nP_s and the floating range of noise signal, it can be inferred that when n is satisfied:

$$n \geq 8(\frac{n_\alpha P_n}{P_s})^2 \tag{10}$$

The probability of mixing signal energy and noise signal energy is $1 - \alpha$. At the same time, the mixing probability at different sampling points can also be calculated:

$$\rho = Q(\frac{\sqrt{2}P_s}{2\sqrt{2}P_n}) \tag{11}$$

According to the equations (10) and (11), the mixing degree of mixed signal and noise signal can be controlled according to the selected sampling frequency.

The significance of mixing degree is that mixing degree is the upper limit of the classification model before adding new features. When the classification model is simple, we can approach this upper limit infinitely by adjusting the model parameters. Therefore, the meaning of calculating the relationship between sampling points and promiscuity is that the sensing performance can be known and controlled by adjusting the sampling frequency.

3. SIMULATION EXPERIMENT RESULTS AND ANALYSIS

In this section, our work is mainly divided into the test of two characteristics of regional model: spectrum efficiency and adaptability.

Suppose P_{s1} and P_{s2} are 20W and 5W respectively, A and ε are 125dB and 35dB respectively, P_n is -104dBm, and τ is 3dB. Set the step size as 1km, the cumulative interference distribution of cognitive base stations at different distances was shown in Figure 3. When the distance is more than 40km, the cumulative interference per 1km is lower than 1% of the interference threshold, so it is reasonable to set the max boundary of the white region to 40km.

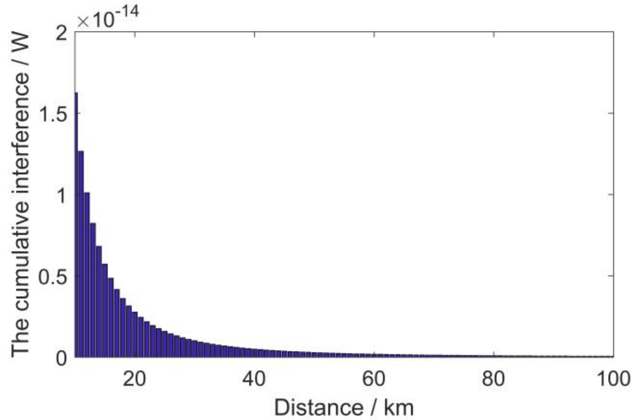

Figure 3. The cumulative interference distribution of cognitive base stations.

And then, spectrum utilization was tested. In order to reflect the spectrum utilization, the concept of total bandwidth resources T was proposed:

$$T = \sum_{i=1}^{n} B_i F_i \tag{12}$$

The total bandwidth resources reflect the spectrum utilization. B is the bandwidth and F is the occupancy probability of frequency band. Set the average occupancy probability P_0 of the frequency band is 0.5, and the probability P_1 of the frequency band meeting the requirements of the black area is 0.1. Figure 4 displayed the relationship between gray region, white region and black region in different region model and the total resources in a single primary base station region were compared with references[8-9], as shown in Figure 5.

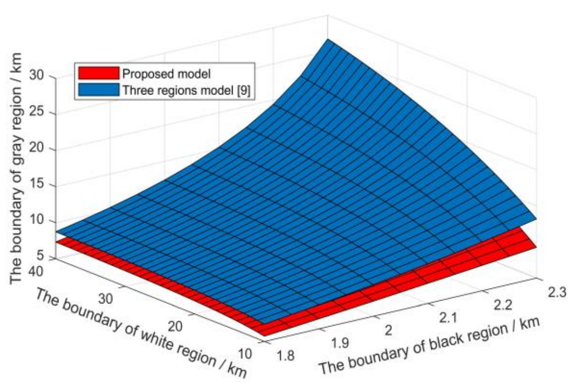

Figure 4. The gray region boundary with white region and black region.

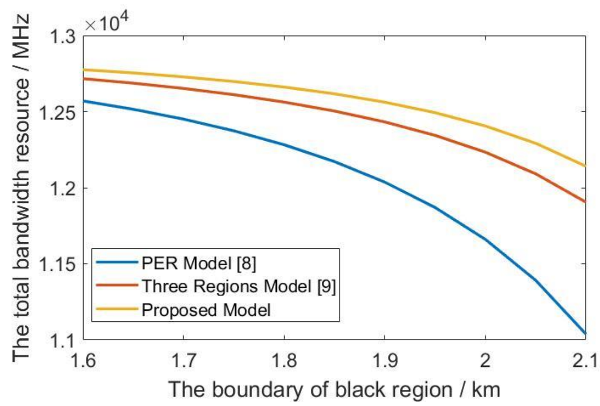

Figure 5. The total bandwidth resource of regions.

It can be seen that the gray region boundary of proposed regional model is significantly lower than that of reference[9], which means more area of white region, so it has higher total bandwidth resources. The throughput of the system can be increased by 9% and the advantages becomes more obvious with the increase of the boundary of black region, because the boundary calculation of the proposed model is more reasonable, and the spectrum resources in the black region are more fully utilized.

Preset a multi primary base stations region with an area of 50km×50km as shown in Figure 6. The distribution area of various frequency bands can be calculated as shown in Table 2. It can be seen that the proposed regional model can be effectively applied to the region of multiple primary base stations.

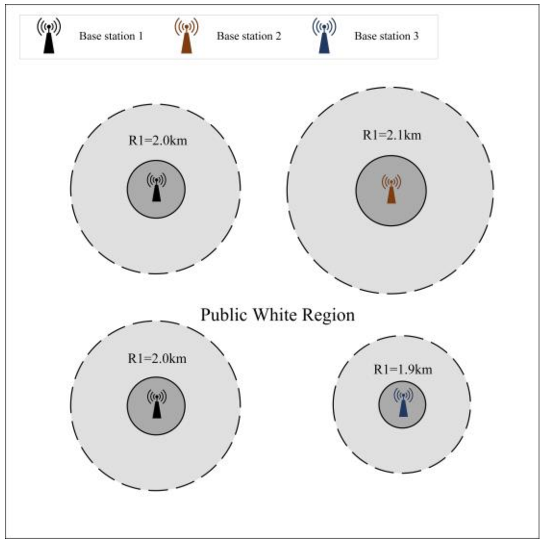

Figure 6. The multiple regional model.

Table 2. Regional distribution of multi primary base stations.

	Black region	**Gray region**	**White region**
Band 1	25.12km^2	688.592km^2	1786.28km^2
Band 2	13.65km^2	538.32km^2	1948.03km^2
Band 3	11.34km^2	230.28km^2	2258.38km^2

Finally, the adaptability of the regional model was tested. SVM was used to classify the data. Set the sampling frequency is 5MHz, sensing time is 0.5ms, the relationship between the accuracy of SVM and the mixing degree of training set was shown in Figure 7.

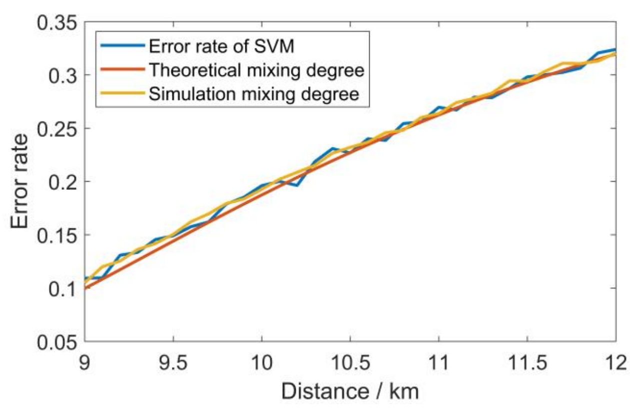

Figure 7. The theoretical mixing degree at different distances and sampling frequencies.

It can be seen that the accuracy of SVM is basically consistent with that of mixing degree, the error between the theoretical mixing degree and the simulation mixing degree is less than 0.48%, so the accuracy of SVM model can be controlled by selecting sampling frequency.

Taken together, these results suggest that the proposed regional model has higher spectrum efficiency and adaptability, which provide insights for the application of geographic information in spectrum sensing.

5. CONCLUSION

In this paper, a spectrum sensing algorithm based on adaptive regional model is proposed. The spectrum efficiency of the regional model is improved by 9% in the single primary base station and successfully applied in the multi primary base station. Meanwhile, the regional model can use geographic information to adaptively adjust the sensing performance of different regions and improve the spectrum utilization. The average difference between actual model accuracy and prediction accuracy is 0.48%, which can effectively control the performance of the classification model to ensure the adaptability of the overall regional sensing performance.

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