A New Dynamic Spectrum Access Technology Based on the Multi-features Model Clustering in the Cognitive Network

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Abstract. In order to fully utilize the scarce spectrum resources, with the development of cognitive radio technologies, dynamic spectrum access becomes a promising approach to increase the efficiency of spectrum usage. In this paper, we consider the spectrum access in wireless networks with multiple selfish legacy spectrum holders and unlicensed users. In order to improve transmission quality for different cognitive users with various services in the cognitive network, a novel dynamic spectrum access technology based on multi-features model clustering is presented. After the model of the sub-channels extracted, these channels are clustered into different spectrum pools using multi-objective clustering algorithm. These channels in white pools are priority to be accessed for cognitive users. Analysis and simulation results show that the access efficiency of channels can be improved for cognitive users.

Keywords: Cognitive radio, multi-features model, spectrum pooling clustering, dynamic spectrum access.

1 Introduction

Recently, regulatory bodies like the Federal Communications Commission (FCC) in the United States are recognizing that current static spectrum allocation can be very inefficient considering the bandwidth demands may vary highly along the time dimension or the space dimension [1]. The spectrum shortage is not scarce physically, but the frequency management policy leads to this misunderstanding.

Cognitive Radio (CR) is a kind of intelligent radio which can constantly senses surrounding environment and changes own situation. According to the external environment change for making decisions, cognitive user adjusts its own communication mechanism (carrier frequency, modulation patterns, transmission power, etc). The biggest advantage is that cognitive users can access network without

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a special authorization by frequency management department and interfering the authorized users. They dynamically access spectrum of the Primary Users (PU) which has been authorized and use the so-called idle spectrum resources by opportunity. This greatly enhances the efficiency of radio resource. As a result, it can not only improve the efficiency of spectrum resource utilization but also enhance the link stability, network coverage and system capacity, obviously.

At present, Dynamic Spectrum Access (DSA) technology has been widely researched which based on the spectrum pooling clustering strategy. DSA permits the cognitive users accessing the band without authorization [2-5].

Spectrum pooling, first presented by Mitola J., allows primary user to lease its band to cognitive users during the time when don't occupy spectrum in order to realize spectrum sharing [3]. When there are many idle channels can be used for cognitive users, how to select channels to obtain better access ability and achieve a better transmission quality is a difficult problem in the current research of cognitive radio. The basic idea of spectrum pooling strategy [3] is to distribute the spectrum outside the special frequency spectrum to different types and then merged into several public spectrum pools, according to ultralow frequency, low frequency, intermediate frequency and high frequency. Spectrum pooling can be divided into several sub-channels. Dr Seidel divided spectrum into excluded space, gray space, and white space. Cognitive users determine their own spectrum access strategies [6] according to the result of spectrum perception. Luwen Z. integrates ideas about how to set up spectrum pools, divide certain areas of spectrum into white spectrum pooling, gray spectrum pooling and black spectrum pooling on the basis of energy detection. Cognitive users mainly access the white channels for better transmission [7]. According to the current research, these methods do not consider cognitive user's various transmission types of channel requirements, but rather doing some simplification assumptions. Comparing to the actual diversity application of network transmission, more attention should be paid on to solve cognitive user's access strategies of dynamic spectrum well.

To satisfy the different needs of channel performance along with different transmission, this paper presents a novel dynamic spectrum access technical based on multi-features model clustering. Once the spectrum pooling is established, cognitive users with different needs can choose these suitable channels to access dynamically, according to the characters of bearing services. The reminder of this paper is organized as follows: The system model of spectrum pooling is described in Section II. In Section III, we formulate dynamic spectrum access strategy based on the multi-features model clustering. The simulation studies are provided in Section IV. Finally, Section VI concludes this paper.

2 System Model

2.1 Spectrum Pool Model

Based on the channel performance requirements of different transmission types, cognitive users can improve own multimedia services flexibility and the utilization rate of the spectrum by renting channels in the spectrum pooling by opportunity.

Reference [8] shows that current spectrum allocation policy leads to different frequencies at the same time (place), or the same frequency at different time (place) occupied degree uniform. Considering hardware restrictions of the terminals and cost constraint, cognitive users should focus on some specific frequencies according to transmission services types. In the following analysis, we assume that cognitive users only focus on n sub-channels $F=\{f_i \mid i=1,2,\cdots,n\}$ generally. According to certain classification rules, the sub-channels are divided into spectrum pooling $P=\{p_i \mid i=1,2,\cdots,k\}$, here $k \le n$, and each channel in spectrum pooling has an approximate performance to satisfy current cognitive user's transmission needs. The model of this spectrum pooling shows in Fig 1.

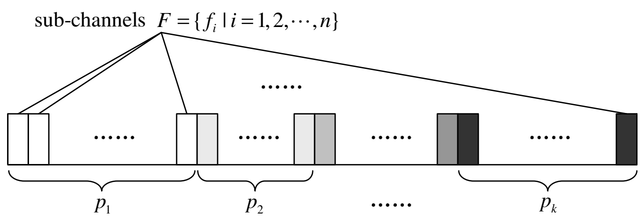

Fig. 1. This shows a model of the spectrum pooling, which includes n sub-channels $F=\{f_i \mid i=1,2,\cdots,n\}$. According to certain classification rules, the sub-channels are divided into spectrum pooling $P=\{p_i \mid i=1,2,\cdots,k\}$, here $k \le n$, and each channel in spectrum pooling has an approximate performance to satisfy current cognitive user's transmission needs.

The bearer ability of spectrum pooling for different cognitive users' transmission needs declined accordingly. (1) Spectrum pooling (white space) is suitable for the current needs of cognitive users' transmission. (2) Spectrum pooling p_b ($b=2,3,\cdots,k-1$, gray space) partly meet the needs, due to the low energy authorized users and interference occupation. And (3) Spectrum pooling p_k (black space) cannot be used in cognitive users' services transmission, because of the high energy of and interference occupation to authorized users.

Using various spectrum senses, estimation and analysis technologies, cognitive users realize the observation to the available channel performance. Once the establishment of spectrum pooling, they formulate the spectrum access strategies to choose sub-channels of white spectrum pool, so that a better services transmission performance can be gotten.

2.2 Multi-features Model

To describe the dynamic characters of the cognitive network, features of each sub-channel should defined according to time variation and environment changes, including activity of primary user, frequency band and bandwidth, etc. Therefore, features such as interference grade, channel error ratio, path loss, link layer delay and holding time are introduced to explain the performance of certain channels. Reference [9] gives these common features to character channel performances.

(1) *Interference threshold* H : the superior limit of signal power that cognitive users are allowed to transmit, which is determined by the interference degree of the main user's receiving end.

(2) *Path loss* L : the amount of loss caused by propagation environment introduction between transmitters and receivers. Path loss increases following the working spectrum location. Similarly, increment of transmission power can decrease path loss, but will cause greater interference to other users.

(3) *Error ratio* E : index that is measured data transmission accuracy within the time specified. According to different modulation modes and interference levels, channel error ratio would be different.

(4) *Link layer delay* D : To address different path loss, wireless link error, and interference, different types of link layer protocols are required at different spectrum bands. This results in different link layer packet transmission delay.

(5) *Holding time* T : Holding time refers to the expected time duration that the CR user can occupy a licensed band before getting interrupted. Obviously, the longer the holding time, the better the quality would be.

Owing to the diversity of cognitive user transmission services, features of sub-channel are required to synthesized to evaluate its performance and to guide the cognitive users to create dynamic access strategies of channels. To character the transmission features of available channels dynamically, here a multi-features model $M(f)$ of sub-channel f is established.

$$M(f)=\left[I^1,I^2,\cdots,I^j,\cdots,I^m\right],\ 1\le j\le m. \tag{1}$$

The multi-features model includes *m* features, I^j refers to the first j feature of the channel. Here, both I^j and m are variables, and the combination includes these features that characterize the sub-channels mostly to services be transmitted. For the *n* sub-channels $F=\{f_i \mid i=1,2,\cdots,n\}$, the multi-features model can be expressed as a matrix by size of $n\times m$, $M_{n\times m}(F)=[I_i^j]_{n\times m}$, $1\le i\le n$, $1\le j\le m$,

$$M_{n\times m}(F)=\begin{bmatrix} I_1^1 & I_1^2 & \cdots & I_1^m \\ I_2^1 & I_2^2 & \cdots & I_2^m \\ \vdots & \vdots & \ddots & \vdots \\ I_n^1 & I_n^2 & \cdots & I_n^m \end{bmatrix}. \tag{2}$$

Where, I_i^j refers to the first j feature of the sub-channel. As a matter of convenience to describe below, the row vector $M_{i\bullet}=[I_i^1,I_i^2,\cdots,I_i^j,\cdots I_i^m]$ can be seen as one sample of the model M , column vector $M_{\bullet j}=[I_1^j,I_2^j,\cdots,I_i^j,\cdots I_n^j]^{\mathrm{T}}$ as a characteristic or quality.

3 Dynamic Spectrum Access Strategy Based on the Multi-features Model Clustering

3.1 Multi-objective Clustering Algorithm

The objective of cluster analysis is the classification of objects according to similarities among them, and organizing of data into several groups. Clustering techniques are among the unsupervised methods, they do not use prior class identifiers.. The main potential of clustering is to detect the underlying structure in data for classification and pattern recognition. The data are typically observations of some physical process. Each observation consists of n measured variables, grouped into an m-dimensional row vector $\mathbf{x}_i = [x_{i1}, x_{i2}, \cdots, x_{im}]^{\mathrm{T}}$, $\mathbf{x}_i \in \mathbf{R}^n$. n observations is denoted by $\mathbf{X} = \{\mathbf{x}_i \mid i = 1, 2, \cdots, n\}$, and is represented as an $n \times m$ matrix:

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{m1} \\ x_{21} & x_{22} & \cdots & x_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}. \tag{3}$$

The clustered data $\mathbf{X}$ can be described as $\mathbf{U} = [\mu_{ij}]_{n \times k}$, meeting the condition in (4):

$$C_k = \{\mathbf{U} \in \mathbf{R}^{n \times k} \mid \mu_{ij} \in 0, 1, \forall i, j; \sum_{j=1}^{k} \mu_{ij} = 1, \forall i; 0 < \sum_{i=1}^{n} \mu_{ij} < n, \forall j\}. \tag{4}$$

Contrast with multi-features model $M_{n \times m}(F)$, the row vector $\mathbf{x}_i = [x_{i1}, x_{i2}, \cdots, x_{im}]^{\mathrm{T}}$ of $\mathbf{X}$ corresponds to features model of sub-channel i, and the column vector (property) corresponds to a feature of the channel $F = \{f_i \mid i = 1, 2, \cdots, n\}$. Multi-objective clustering algorithm are used to establish spectrum pooling, based on the multi-features model of the channel that was paid attention by cognitive user according to certain rules.

3.2 Dynamic Spectrum Access Based on the Multi-features Model Clustering

The multi-objective clustering algorithms, each method has its own properties and scopes of application. To achieve the target that cognitive users get a high speed of communication, *K*- Means Clustering method can be used here that is widely used for massive dataset with fast convergence rate. However, this method is limited to sensitiveness initial clustering center and will produce uncertain results, due to selecting initial clustering center randomly in the most common applications. This paper proposed a feature space partition method to calculate an optimized initial clustering center for *K*-Means clustering algorithm and achieved spectrum pooling rapidly with multi-features model.

Taking the multi-features model $M_{n\times m}(F)=[I_i^j]_{n\times m}$ and number of spectrum pooling k of $F=\{f_i \mid i=1,2,\cdots,n\}$ as input, the spectrum pooling access strategy algorithm based on improved K-Means clustering algorithm is as follows.

(1) *Partition of Feature Space*

Multi-features model of channel F is given, features space W^j of F can be calculated by features space $M_{\bullet j}$ ($j=1,2,\cdots,m$),

$$W=\prod_{j=1}^{m}W^j=\prod_{j=1}^{m}[I_{\min}^j,I_{\max}^j]\,. \tag{5}$$

Here, $I_{\min}^j$ and $I_{\max}^j$ are the minimum and maximum characteristics values respectively. According to the classification number k, the features space of I^j can be divided into k subinterval W_b^j without crossing,

$$W_b^j=(I_{\min}^j+\frac{(b-1)(I_{\max}^j-I_{\min}^j)}{k},\ I_{\min}^j+\frac{b(I_{\max}^j-I_{\min}^j)}{k}],\ b=2,3,\cdots,k\,. \tag{6}$$

Especially, the left side of W_1^j is closed interval when $b=1$ to maintain the integrity of the parameters space.

(2) *Multi-Features Model Coding*

The model $M(f_i)=\left[I_i^1,I_i^2,\cdots,I_i^j,\cdots,I_i^m\right]$ of channel responds to one sequence of binary $(b_i^1,b_i^2,\cdots,b_i^m)$, meeting $M(f_i)\in\prod_{j=1}^{m}W_{b_i^j}^j$, and,

$$I_i^j\in W_{b_i^j}^j,\ j=1,2,\cdots,m\,. \tag{7}$$

Here, this vector can be named code of multi-features model, shown as,

$$B(f_i)=(b_i^1,b_i^2,\cdots,b_i^m)\,. \tag{8}$$

(3) *Calculate the Initial Clustering Centers*

By grouping the multi-features model with same model code into one group G_b^0, the average method are used to calculate the initial clustering center C_b^0 for each set,

$$C_b^0=\frac{1}{n_b}\sum_{i=1}^{n_b}M(f_i),\ b=1,2,\cdots,k\,. \tag{9}$$

Here, n_b is the number of channel contained in G_b^0.

(4) *Spectrum Pooling Clustering*

The distance between channel model $M(f_i)$, $1\le i\le n$ and clustering centers is calculated in (10),

$$d(M(f_i), C_b^t) = \sum_{j=1}^{m} \left\| I_i^j - c_b^j \right\|^2 . \tag{10}$$

Parameter t is iteration of clustering centers, the closest clustering center is classified into group G_b^t.

(5) *Clustering Centers Update*

Calculate new data clustering center through G_b^t obtained by the time t.

$$C_b^{t+1} = \frac{1}{n_b} \sum_{i=1}^{n_b} M(f_i) ,\ b = 1, 2, \cdots, k . \tag{11}$$

Here, n_b is the number of sub-channel. If $C_b^{t+1} = C_b^t$, $b = 1, 2, \cdots, k$, clustering ends and enters spectrum dynamic access strategies stage (6), or turn to (4) and set $t = t + 1$.

(6) *Dynamic Spectrum Access Strategies*

Once spectrum pooling clustering $p_b = G_b^t$, $b = 1, 2, \cdots, k$, is established, cognitive users formulate channel access strategies to access white spectrum pool to get better transmission performance.

Based on requirements of different services transmission, the cognitive users establish spectrum pooling clustering and access strategy process dynamically.

4 Simulations and Performance Analysis

4.1 Simulations and Experiments

To testify that the proposed adapting multi-features model clustering algorithm can improve the performance of accessing authorized channel for the cognitive users, the following assumptions can be adapted to simulations.

(1) The sub-channels can be accessed for the cognitive users is $F = \{ f_i \mid i = 1, 2, \cdots, n \}$, in other words, $n = 9$;

(2) Assume the channel features are many different combinations including interface threshold (*H*), path loss (*L*), error ration (*E*), link layer delay (*D*), and holding time (*T*) and so on. For a complete analysis of spectrum pooling clustering performance, three simulations with different combination of the features were designed, shown in table 1-3. Meanwhile the forth simulation were used to test dynamic performance of our algorithm.

(3) To simplify the simulation analysis, the number of spectrum pooling clustering was set $k = 3$, respectively corresponding to the white spectrum pooling p_1, gray spectrum pooling p_2 and black spectrum pooling p_3.

The first simulation: Holding time is the key feature to measure channel quality which is also the most concerned channel feature to cognitive users.. The longer the channel holding time is, the better the channel quality can be achieved for cognitive users. Channel holding time is used as the single feature of the first simulation experiment. The channel situation was shown in table 1.

Table 1. Sub-channels utilization for the first simulation

	Sub-channels								
	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
T	16	32	22	45	2	18	21	5	38

The second simulation: Except channel holding time, the channel interference threshold was added. To find the effect of two features on the spectrum clustering result, the specific channel features are shown in table 2.

Table 2. Sub-channels utilization for the second simulation

	Sub-channels								
	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
T	16	32	22	45	2	18	21	5	38
D	0.8	0.9	0.4	10	0.4	0.5	0.5	0.1	0.9

The third simulation: The third simulation experiment designed contained five kinds of common channel features, including holding time and interference threshold used in the first and the second simulation. The result was shown in table 3.

Table 3. Sub-channels utilization for the third simulation

	Sub-channels								
	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
T	16	32	22	45	2	18	21	5	38
D	0.8	0.9	0.4	10	0.4	0.5	0.5	0.1	0.9
L	0.02	0.08	0.5	0.01	0.3	0.1	0.01	0.3	0.04
E	1	1	10	2	6	8	12	4	2
H	1.0	0.2	2.3	0.02	0.7	0.4	0.08	1.2	0.1

The fourth simulation: In order to inspect effectiveness of the algorithm further, channel usable time obeys the uniform distribution with the parameters of $(T_{\min} = 0, T_{\max} = 5)$. The spectrum pooling cluster was simulated 1024 times and the channel holding time was re-generated each simulation. Here the average holding time of all the spectrum pool is presented.

4.2 Simulation Results and Performance Analysis

In the environment given in 4.1, four experiments are simulated for $F = \{ f_i \mid i = 1, 2, \cdots, 9 \}$ using Matlab R2006. The results of spectrum pooling clustering were obtained.

The spectrum pooling clustering result for the first experiment is:

$$p_1 = \{f_2, f_4, f_9\},\ p_2 = \{f_1, f_3, f_6, f_7\},\ p_3 = \{f_5, f_8\}.$$

The average holding time of white spectrum pooling p_1 is 38.33, is bigger than the gray and black spectrum pooling of 19.25 and 3.5. Then, cognitive users formulated the accessing strategy according to the generating spectrum pooling. The available sub-channels in white spectrum pool p_1 will be chosen firstly as the high-performance transmission channels. The first simulation experiment can get similar results using the spectrum pooling clustering method referred in document [4]. But the multi-characteristic parameters spectrum pooling, such as the second and third simulation experiment designed here, cannot be achieved.

The spectrum pooling results for the second simulation experiment is:

$$p_2 = \{f_1, f_2, f_3, f_6, f_7, f_9\},\ p_1 = \{f_4\},\ p_3 = \{f_5, f_8\}.$$

And the clustering result for the third simulation is:

$$p_1 = \{f_2, f_9\},\ p_2 = \{f_4\},\ p_3 = \{f_1, f_3, f_5, f_6, f_7, f_8\}.$$

Contrasting results among these three simulations, more channel features have greater effects on the spectrum pooling clustering. The comparison of average holding time between three simulations is shown in Fig 2. After clustering, the average holding time has greater changes. Due to increasing the number of features, the average holding time of spectrum pooling p_1 was decreased. Because the link layer delay of channel f_4 is big enough, this channel was grouped into other spectrum pooling. Though the average holding time of white spectrum pooling was shorter, it is longer than the time of black spectrum pooling.

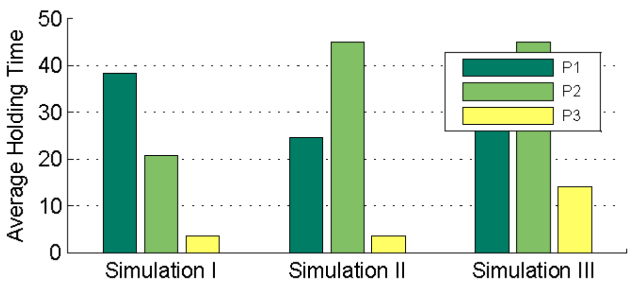

Fig. 2. This shows Average Holding Time of the three experiments, in which blue bars are the first simulation results, green bars are the second results and red bars are the third results

Spectrum pooling clustering of dynamic spectrum was given in the forth simulation. The front 64 times simulation results of average holding time are plotted in Fig 3. The average holding time of white spectrum pooling is longer than other spectrum pools.

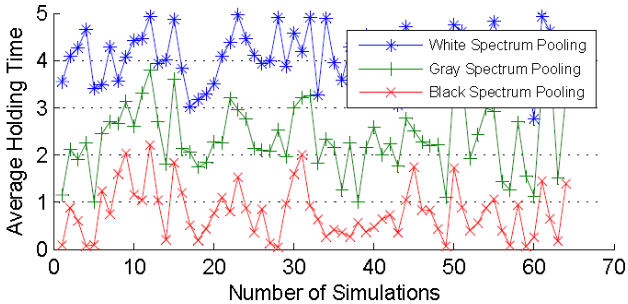

Fig. 3. This shows dynamic simulation results of spectrum spooling clustering. The average holding time of white spectrum pooling is longer than other spectrum pools.

5 Conclusion

To present an universal and accuracy dynamic accessing dynamic technology based on spectrum pooling, the multi-feature model and K-Means clustering are used in this paper. Combining the efficient primary users detection technologies, such as circle-steady detection and joint detection the spectrum features was characterized comprehensively using the multi-features model of sub-channels. Thus the spectrum pooling clustering provides a more accurate and reliable criteria for cognitive users when accessing channels. Also a new idea of the spectrum assigning is given: the sub-channels can be clustered according to the different demands of different cognitive users. According to the demands of services quality, cognitive users choose a more suitable sub-channel to access dynamically and the transmission performance of the whole system can be improved greatly.

The different channel features have the same effect to the spectrum pooling clustering. But actually, they have different influence coefficients to different services of cognitive users. Using an influence coefficient in the channel multi-features model in our future research, the accuracy of the spectrum clustering can be improved. And a more accurate and reliable basis is given for cognitive users to access sub-channels.

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