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Dynamic Spectrum Access Technology Based on Fuzzy Clustering Algorithm

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Abstract. In order to improve the spectrum utilization efficiency, a dynamic spectrum access technology based on fuzzy clustering algorithm is proposed to satisfy the multiple services need of cognitive users. Firstly, this algorithm establishes the multi-goals channel model of accessible channels to divide the spectrum pool accurately. Based on the multi-goals channel model, a spectrum pool partition method for multi-objective clustering is proposed. This algorithm has the ideal users' satisfaction and higher spectrum access efficiency. Analysis and simulation results show that the improved multi-objective clustering algorithm is more accurate and has faster spectrum access rate compared with the previous algorithms. This algorithm can divide the spectrum pool more effectively and improve the spectrum utilization efficiency.

Keywords: cognitive radio, dynamic spectrum access, fuzzy clustering, multi-goals model, spectrum pool

1 Introduction

With the rapid development of the Internet of things and the continuous growth of the economy, the demand for wireless spectrum resources is increasing correspondingly [1-3]. The resources allocated to new industries and new technologies are in short supply. The related research shows that the main problem in wireless communication technology is the low utilization of spectrum [4-5]. Cognitive radio technology [6] has the ability of environmental sensing and self-learning [8-11]. By collecting the information of the surrounding environment, it can analyze, understand and judge the change of environment [12]. Then it can adjust communication mechanism in real time, therefore, it is convenient for cognitive users to access spectrum dynamically [13-15]. Dynamic spectrum access technology can be briefly summarized that the cognitive users constantly search for available spectrum holes for their information transmission [16-18]. First of all, the cognitive user can only transmit the information when the primary user does not use its spectrum. Secondly, when the primary user is communicating, the cognitive user must quit the current spectrum to avoid interference of the primary users [19].

When there are numerous idle channels, the major and difficult problem is how can cognitive users choose the appropriate channel and access it fast [20]. At present, the dynamic access of the spectrum is based on the spectrum pool strategy in a lot of researches. Professor J Mitoma is the presenter of the spectrum pool strategy and the main idea is: when cognitive users use sensing technology to find that the primary users are not working and the spectrum is at the idle condition, cognitive users can access their channels to achieve multiple uses of the spectrum [21]. In literature [22] the spectrum is divided into black, gray and white space, and cognitive users make spectrum decision through spectrum sensing. Zhao

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et al. subdivides the spectrum into sub channels and divides the channels according to the gray index size into three spectral pools: white, gray and black [5]. The cognitive users finally choose white spectrum pool to access [7]. It not only reduces the collision and blocking for the primary users, but also speeds up the communication rate of Cognitive users. Literature [23] proposes a game algorithm that shares the spectrum between cognitive users and primary users and the cognitive users by cognitive service types of mission-critical users and high-real-time business users. Cognitive user needs, the main service revenue and the satisfaction of cognitive services are the optimization goals, and the utility of the cognitive users is guaranteed to be maximized during the game. However, division process is complicated in the algorithm and the access efficiency need to be improved. In [24], the carrier sense multiple access method is introduced in communication, and different listening mechanisms are adopted according to the different needs of users. By determining the action of the primary user to select the corresponding backoff mechanism, this algorithm proposes a priority-based non-authorization users spectrum access plan. Based on cognition, a Markov model based on queuing theory is constructed. Through the matrix analysis, the performance index of the system is obtained. Finally, the best backoff time for high-priority unauthorized users is obtained when the system throughput reaches the maximum. However, this kind of back-off mechanism needs to be improved in network fairness. Literature [25] will recognize the cognitive user transmit power as the priority perception factor for the inter-user traffic transmission. Based on the collaborative characteristics of the primary and cognitive users, the cooperative dynamic power control model is established by introducing the differential game for the cumulative interference constraint problem generated by the primary user system. The non-cooperative dynamic power control is established compared with the non-cooperative cognitive users. The model has good performance in throughput and transmit power. However, because the users need to adjust the power continuously according to the current service transmission condition, the iteration time of the algorithm is long. In literature [26], A blind multi-band spectrum sensing (BMSS) method based on K-means clustering (KMC) is proposed. When the user information, channel communication condition and current environment condition is unknown, the KMC algorithm firstly divides the channels into occupied channel sets (OSS) and unoccupied channel sets (ISS). After the channel is divided according to the character of the channel, the number of occupied channels and the location information are obtained according to the primary user who is communicating. The method has better detection performance in low SNR and small sample scenarios. The detection performance is robust when the noise variance is uncertain or inconsistent. In literature [27], the algorithm divides the channels into different clusters according to the correlation between them, and then predicts the channel state according to clusters. In the prediction process, the detection information between multiple secondary users is merged and compared, which improves the accuracy of detection. The algorithm has the better frequency prediction convergence and effectively reduces the prediction delay.

The related literature studies the spectrum division and the dynamic access strategy of the spectrum pool, but they are not accurate enough, and cognitive users still need to improve the spectrum access rate [28]. In this paper, we propose a dynamic spectrum access technology based on fuzzy clustering algorithm. Firstly we establish a multi-objective matrix model of accessible channels and using a multi-objective clustering method to divide the spectrum accurately. Therefore, cognitive users can access the suitable channels dynamically. Secondly we propose an improved C-means clustering algorithm. It can get a relatively reasonable global clustering center, and then use this center as the initial clustering point of the algorithm. It can make spectrum classification more accurate and significantly improves the convergence speed compared with other algorithms. Finally, in order to achieve rapid clustering of spectrum pools by the channel multi-objective matrix model, this algorithm uses the information granularity principle to determine the number of clusters and judge the quality of the clustering results by the information particle coupling degree and the separation degree.

2 System Model

2.1 The model of Spectrum Pooling

The concept of spectrum pool was first proposed in, which mainly focus on the existing authorization system and make no change on it. When there are idle spectrums in the spectrum pool, the cognitive user can access an appropriate idle channel according to the type of the transmission service. In this way, spectrum can be reused and the transmission rate of cognitive users is also improved. The literature indicates that the current spectrum allocation strategy causes most of the spectrums to be not fully utilized and only small parts are used frequently. Only in the following two cases does the cognitive user have to perform the second switching of the spectrum.

When the primary users access the channel again, the cognitive users must immediately quit the channel and quickly sensing the next available channel to continue working. When channel quality decrease by interference, the cognitive users need to switch spectrum to ensure the primary users work normally. Due to the constraints of many practical conditions, the cognitive users only pay attention to some specific frequency bands in the spectrum switching process and divide the *m* sub-channels of them ($F = \{ f_i \mid i = 1, 2, \dots, m\}$) into different spectrum pools W_j ($j = 1, 2, 3, \dots, k, k \le m$). The performance of the W_1 to W_k spectrum pool is gradually degraded. (1) Spectrum pool W_1 is best suited for cognitive user access due to its good channel quality. (2) Spectrum channel W_a ($a = 2, 3, \dots, n, n < k$) has poor channel quality due to interference in most of the time and occupied by low power. (3) Spectrum channel W_k has the lowest channel utilization because that it is mostly occupied by high power radio frequency energy. The cognitive users access the channel with the best channel quality by constantly sensing, estimating, and analyzing the usage of all channels. By establishing a spectrum pool and selecting a spectrum pool (white spectrum) to access, performance of high-quality transmission service can be achieved.

2.2 Channel Model

In order to continuously satisfy the user's diversity choices for different channels, we consider the different performance indicators of the channels to establish a multi-objective matrix model of the channel.

Assumed spectrum domain as: $W(f) = [w_1, w_2, \dots, w_n]$ and the spectrum of each cluster is represented by *m* channels characteristics:

$$w_i = [x_{i1}, x_{i2}, \dots, x_{im}] \ (i = 1, 2, \dots\dots, n) \quad \textbf{(1)}$$

The corresponding raw data matrix is:

$$W_{n\times m}(F) = \begin{pmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{pmatrix} \quad \textbf{(2)}$$

where x_{ij} represents the performance parameter *j* of the channel *i* ($1 \le i \le n$). The row vector $W_i = [x_{i1}, x_{i2}, \dots, x_{in}]$ of $W_{n\times m}(F)$ is a sample of WW. Column vector $W_j = [x_{ij}, x_{ij}, \dots, x_{nj}]^T$ represents a channel performance of *W*. In this way, the multi-objective matrix $W_{n\times m}(F)$ can represent all features of the n sub-channels ($F = \{f_i \mid i = 1, 2, \dots, n\}$) which the cognitive user focus on.

Because several feature parameters are selected to describe the channel characteristics, the meanings and units of different feature parameters are also different. In order to facilitate the processing of data, the parameters of each line are normalized to make the data fluctuates within the range of 0-1. Formula is as follows:

$$x_{ij} = \frac{x_{ij} - x_{i\min}}{x_{i\max} - x_{i\min}} \quad \textbf{(3)}$$

which $x_{i\max}$ is the maximum of row vector $W_{i.}$, $x_{i\min}$ is the minimum of row vector $W_{i.}$, The normalized multi-objective matrix is obtained by normalizing the original data matrix:

$$\overline{W}_{n\times m}(F) = \begin{pmatrix} \overline{x}_{11} & \cdots & \overline{x}_{1m} \\ \vdots & \ddots & \vdots \\ \overline{x}_{n1} & \cdots & \overline{x}_{nm} \end{pmatrix} \quad \textbf{(4)}$$

3 Clustering of Spectrum Pool

3.1 An Improved C-means Clustering Method

Clustering method is to classify different objects according to a certain character. At the first, selecting c objects randomly as the initial clustering center, then using iterative method to assign the selected objects to the corresponding classifications. The similar objects are classified into the same cluster, and dissimilar objects are classified into different clusters. The number of clusters c of the original algorithm is obtained from the prior information, which c objects are randomly selected as the initial cluster center from the sample set. Because the change of the cluster center has a great influence on the clustering result, an improved C-means clustering algorithm is proposed. By changing the selection method of the initial clustering center, the clustering result is obviously optimized. The method process is as follows:

(1) Calculate the Euclidean distance $d(f_i, w_j)$ between two samples in w_i, $d(f_i, w_j) = \| w_i - w_j \|$, and finding two closest samples. Then put them into a new set and get a new set A_1.

(2) Calculate the Euclidean distance between each sample and each data object in set U, and then find out which sample's distance between data object is closest to the distance in A_1. After that, put it into the set A_1 until the data of set reaches a certain threshold.

(3) Find out the nearest two samples in the set U to get another sample set, and repeat the above operations until c sample sets are obtained.

(4) Find the mean of c samples, and then produce c initial clustering centers.

Since the number of clusters in C-means clustering algorithm is set by a priori information, this paper introduces the principle of granularity to determine the number of clusters [10]. Clustering for different granularities corresponds to the sets division of different particle points, while constraining them by a validity function. The quality of clustering is judged by the degree of coupling of information particles and the degree of separation. If the degree of coupling changes smaller, it indicates that the compactness inside the cluster becomes more reasonable. If the degree of separation changes larger, it indicates that the separation between different categories becomes more reasonable.

Coupling degree of information particle is as follows:

$$Hd(c) = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n} u_{ij} d_{ij}{}^{2} \tag{5}$$

Separation degree of information particle is as follows:

$$Fd(c) = \frac{\sum_{i,j=1;i\neq j}^{c} d_{ij}^{2}}{\left[c(c-1)\right]/2} \tag{6}$$

According to the coupling degree of information particle and the separation degree of information, Validity function is:

$$YD(c) = \beta \times c \times Hd(c) + (1-\beta)/Fd(c) \tag{7}$$

In this formul*a*, β=0.6, 1-β=0.4. Smaller *YD(c)* values represent better clustering results. The c value corresponding to the minimum value of *YD(c)* is the optimal number of clusters.

3.2 The Clustering and Division for Spectrum Pool

There are a wide variety of clustering algorithms. Because different algorithms have different advantages, so they are used in different situations. This paper proposes an improved C-means clustering algorithm, which has the advantages of rapid convergence, higher accuracy, and wide application. It can get a relatively reasonable global clustering center, and then make this center as the initial clustering point of the algorithm. It can make spectrum classification more accurate and significantly improves the convergence speed compared to previous algorithms. In order to achieve rapid clustering of spectrum pools by the channel multi-objective matrix model, this algorithm uses the information granularity principle to determine the number of clusters and then judge the quality of the clustering results by the information particle coupling degree and the separation degree.

The input of the spectrum pool clustering algorithm is the number of spectrum pool cluster *C* and the multi-object matrix model of channel $\overline{W}_{n\times m} = [\overline{X}_{ij}]$ The output is the channel classification result.

The specific implementation of spectrum pool clustering algorithm is as follows:

The multi-object matrix model of channel $W(f)$ is $\overline{W}_{n\times m}(F) = \begin{pmatrix} \overline{x}_{11} & \cdots & \overline{x}_{1m} \\ \vdots & \ddots & \vdots \\ \overline{x}_{n1} & \cdots & \overline{x}_{nm} \end{pmatrix}$, and there are *m* features in $\overline{w}_i$ of $\overline{W} = [\overline{w}_1, \overline{w}_2, \overline{w}_3, \cdots, \overline{w}_n]$, which is $\overline{w}_i = [\overline{x}_{i1}, \overline{x}_{i2}, \cdots, \overline{x}_{im}]\,(i = 1, 2, \cdots, n)$ and classifying *W* into *c* ($2 \le c \le n$). After clustering, the data set *W* is divided into subsets $U = [u_{ij}]_{n\times c}$, the following constraints are met.

$$V_c = \left\{ \sum_{j=1}^{c} u_{ij} = 1; U \in R^{n\times c} \middle| u_{ij} \in 0,1,i,j \right\} \quad \textbf{(8)}$$

The specific steps for spectrum pool clustering are as follows:

(a) Initialization parameters: First select *n* sub-channels from *N* sub-channels, set initial cluster number $C_{\max} = \sqrt{n}$, iteration stop threshold *ε*, maximum iteration number and weight factor *α*, and initial value $L = 0$.

(b) Calculation of initial channel clustering center: Using an improved *C*-means clustering algorithm to obtain the initial channel clustering center and then obtain and output channel clustering results.

(c) Update channel classification matrix *U*:

$$U : u_{ij} \begin{cases} \dfrac{\|\overline{\mathrm{x}}_{\mathrm{i}} - \mathrm{v}_{\mathrm{j}}\|}{\sum_{j-1}^{c} \| \overline{x}_i - v_j \|} & \|\overline{\mathrm{x}}_{\mathrm{i}} - \mathrm{v}_{\mathrm{j}}\| > 0 (1 \le \mathrm{j} \le \mathrm{c}) \\ 1 & \|\overline{\mathrm{x}}_{\mathrm{i}} - \mathrm{v}_{\mathrm{j}}\| > 0 (1 \le \mathrm{j} \le \mathrm{c}) \\ 0 & \|\overline{\mathrm{x}}_{\mathrm{i}} - \mathrm{v}_{\mathrm{j}}\| = 0 \end{cases} \quad \textbf{(9)}$$

(d) Update channel cluster center *V*:

$$V_i = \frac{\sum_{c=1}^{n} \overline{x}_c \times {u_{ic}}^{\delta}}{u_{ic}} \quad \textbf{(10)}$$

m is the fuzzy weighted index, where *m*=2.

(e) if the upper limit of *ε* is not reached, the values of *U* and *V* will be recalculated.

(f) Calculate the effective function *YD(c)* and save this value.

(g) Calculate the distance between every two channel clusters and combine the two smallest clusters into one. Then *C*-1 channel clustering centers will be obtained.

(h) Let *C*=*C*-1, if *C*>1, set *L*=0, turn to (c), otherwise, turn to (i).

(i) Select the minimum value of the effective function *YD(c)* as the optimal clustering result. In order to obtain better service output performance, the cognitive user performs clustering based on the generated spectrum pool, and the white spectrum pool is mainly selected for access.

4 Simulation and Performance Analysis

4.1 Simulation Data and Experiment Settings

In order to verify the impact of this algorithm on the speeding of channel accessing of cognitive users, supposing the number of sub-channels n=9. That is, channel $F=\{ f_i \mid i = 1, 2, 3, \ldots, n\}$ can be accessed by cognitive users. The characteristic parameters of the set channel are different combinations of various parameters such as the interference threshold H, the channel occupation time T, the link layer delay D, the path loss L, and the channel error rate E. The simulation parameters are as shown in Table 1. According to the spectrum allocation model, the cognitive users and the idle spectrum are mapped and matched one by one to complete the spectrum allocation.

Table 1. Simulation parameters

parameters	range of parameters
the channel occupation time/us	[0, 100]
the link layer delay/us	[0, 20]
the channel error rate/es	[1, 50]
the interference threshold/(dBuV/m)	[0, 10]
the path loss *L/dbm*	[-30, -1]
Transport area	250m×250m

This paper designs a combination of three different parameters to analyze the effect of spectrum pool clustering, corresponding to Table 1, Table 2, Table 3 and Table 4.

Table 2. Sub-channel Occupancy of Experiment I

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
T	15	30	20	37	4	17	19	7	45
D	0.9	1.0	0.5	1.0	0.5	0.6	0.5	0.2	8

Experiment II: In order to reflect the effect of increasing feature parameters on spectral clustering, on the basis of experiment I, link delay D, a channel characteristic parameter, was added.

Table 3. Sub-channel occupancy of Experiment II

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
T	15	30	20	37	4	17	19	7	45
D	0.9	1.0	0.5	1.0	0.5	0.6	0.5	0.2	8

Experiment III: Continue to increase the number of characteristic parameters. Added the channel characteristic parameters such as interference threshold H, channel occupancy time T, link layer delay D, path loss L, and channel error rate E, etc. to Experiment III. The specific data is shown in the table.

Table 4. Sub-channel occupancy of Experiment III

	T(us)	*D(us)*	*E(es)*	*H*	*L(dbm)*
f_1	15	0.9	2	1.0	-16.9
f_2	30	1.0	2	0.2	-11
f_3	20	0.5	10	2.4	-2.8
f_4	37	1.0	3	0.02	-20
f_5	4	0.5	7	0.7	-5.2
f_6	17	0.6	9	0.4	-10
f_7	19	0.5	13	0.08	-20
f_8	7	0.2	5	1.1	-5.3
f_9	45	1.5	3	10	-14

In order to simplify the simulation analysis process, the number k of clusters in the spectrum pool is 3. That is, spectrum pools are divided into white spectrum pools w_1, gray spectrum pools w_2, and black spectrum pools w_3.

Experiment I: The available time of channel is the most critical factor in the channel quality measuring and the longer the channel is used by the user, the better the channel quality is. At the same time, it is also the channel feature that most cognitive users are most concerned about. In Experiment I, the available time *T* is used as an experimental parameter in clustering for spectrum pool. The channel occupancy is shown in Table 2.

Experiment IV: In order to further verify the effectiveness of the algorithm, the available duration of the channel *T* obeys a uniform distribution between 0 ~1.

The number of simulation spectrum pool clusters is 1024, and the average number of iterations of the algorithm is obtained according to the number of different users.

4.2 Simulation and Analysis

For the channel $F=\{f_i \mid i=1, 2, 3, \ldots, 9\}$given in Table 1, according to the given *C*-means clustering algorithm, spectrum pool clustering results are easily obtained. Experiment I spectrum pool clustering results are shown in Table 4.

Table 5. Results of Spectrum Pool Clustering In Experiment I

$W(F)$	w_1	w_2	w_3
$W(f_1)$	f_2, f_4, f_9	f_1, f_3, f_6, f_7	f_5, f_8

The average available duration of spectrum pool after clustering was 37, 33, 17.75 and 5.5, respectively. It can be concluded that the average duration of the white spectrum pool is much longer than the gray and black spectrum pools. Cognitive users mainly access the white spectrum pool to obtain high-performance transmission channels.

The following is the result of spectrum pool clustering by setting multi-objective parameters in experiment II, III.

Table 6. Results of Spectrum Pool Clustering in Experiment II

w_1	w_2	w_3
$f_1, f_2, f_3, f_4, f_6, f_7$	f_9	f_5, f_8

Table 7. Results of Spec trum Pool Clustering in Experiment II

w_1	w_2	w_3
f_4, f_4	f_9	$f_1, f_3, f_5, f_6, f_7, f_8$

Fig. 1 shows the comparison results of the average channel available duration of the corresponding spectrum pool obtained by the three simulation experiments. ① Comparing the spectral pool clustering results generated by Experiment I, Experiment II and Experiment III, we can conclude that the different channel parameters produce the different results. ② The average available duration of the spectrum pool p_2 in Experiment II and Experiment III is higher than the average available duration of the spectrum pool p_1 in Experiment I. The reason is that f_9 is clustered into w_2 due to the large interference threshold of f_9, so that the average channel duration of the spectrum pool increased. ③ In the three experiments, the average channel duration of the spectrum pool p_1 is higher than the spectrum pool p_3, which shows that *T* is the main factor affecting the spectrum pool clustering. The results show that multi-objective parameter model clustering can meet the requirements of different channels performance and achieve high-performance channel division.

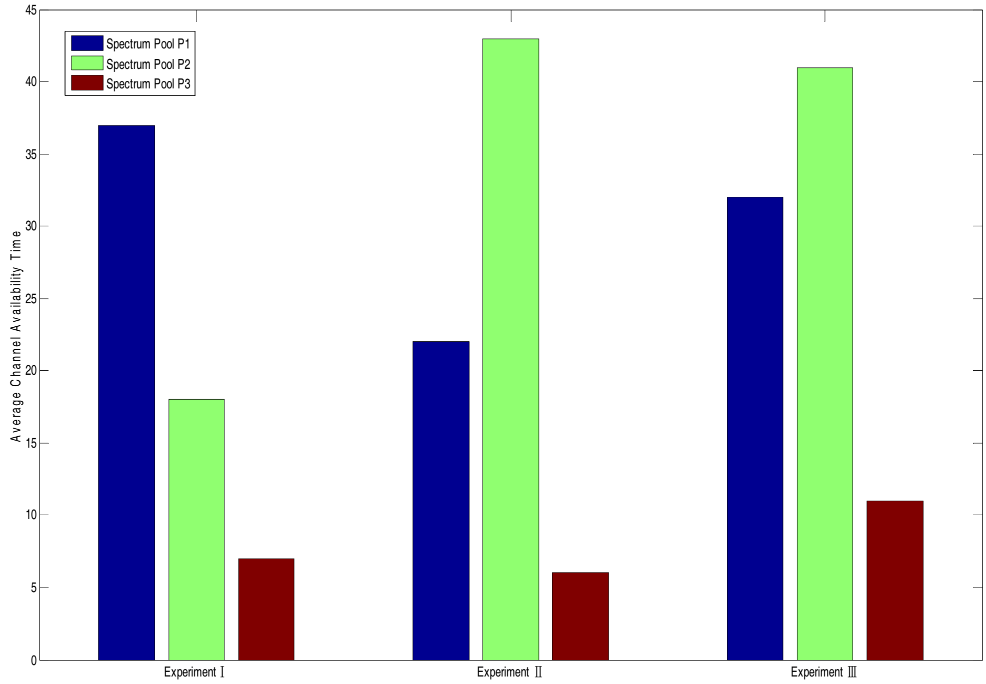

Fig. 1. Comparison of "average channel duration" of spectrum pool clustering average channel available duration

Experiment IV shows the dynamic changes of spectrum pool clustering clearly. Fig. 2 shows the convergence speed of the algorithm of different number of users. The average number of iterations of the improved algorithm presented in this paper is less than the algorithms in literature [26] and literature [27]. When the spectrum information is known, users can make favorable choices faster and make themselves more profitable.

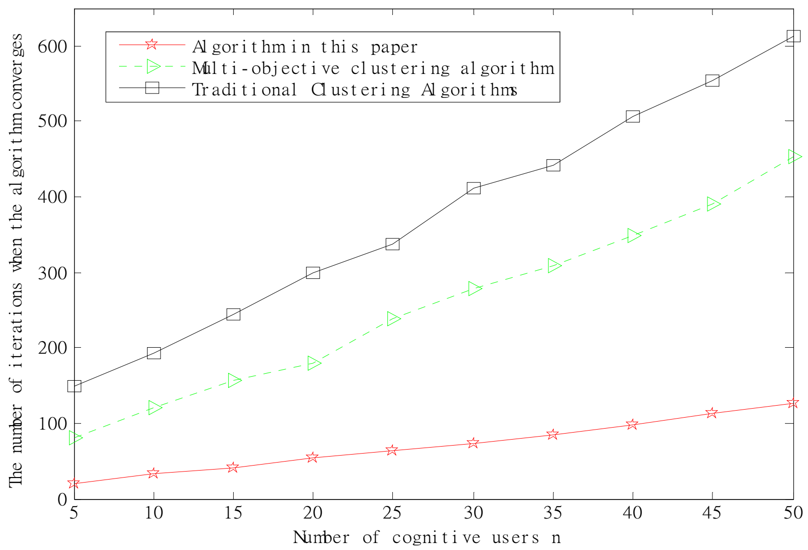

Fig. 2. The number of iterations when the algorithm converges

Compared with the convergence speed of the algorithm, it can be seen from Fig. 3 that the throughput of the system is improved with the increasing of users. The throughput of this algorithm is significantly higher than the algorithms in literature [26] and literature [27]. Experiments have verified that the algorithm sped up the convergence speed, reduced the perceived time, enabled users to make decisions faster and improved the utilization of spectrum.

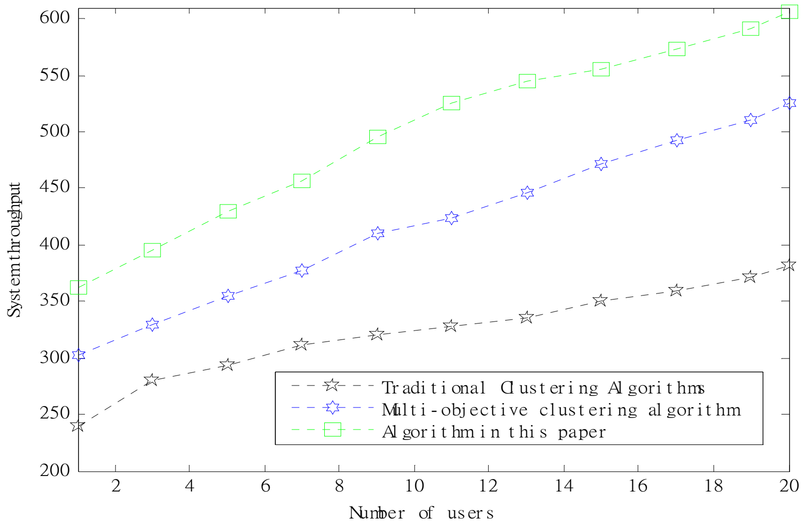

Fig. 3. Comparison of two algorithms system throughput for different number of users

As shown in Fig. 4, Compared with the blocked probability for different number of users, this algorithm reduces the blocked probability of black, gray and white pool with the increasing of users. Experiment verifies that the algorithm improved the successful access rate.

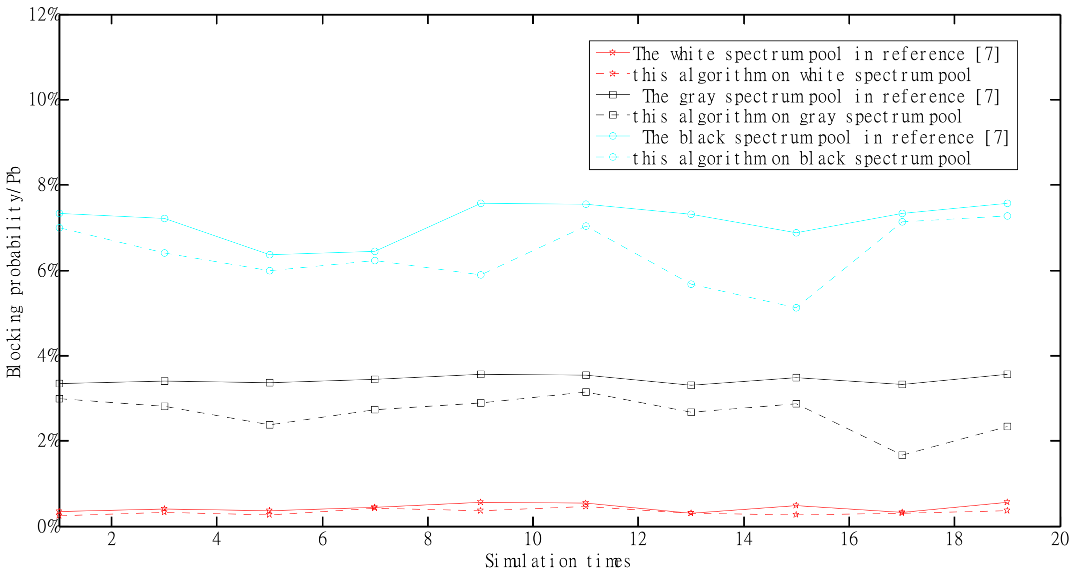

Fig. 4. Comparison of the blocked probability for different number of users

As shown in Fig. 5, Compared with the access efficiency for different number of users, the access efficiency is higher than literature [7]. Experiment verifies that this algorithm improves the access efficiency of black, gray and white pool with the increasing of users.

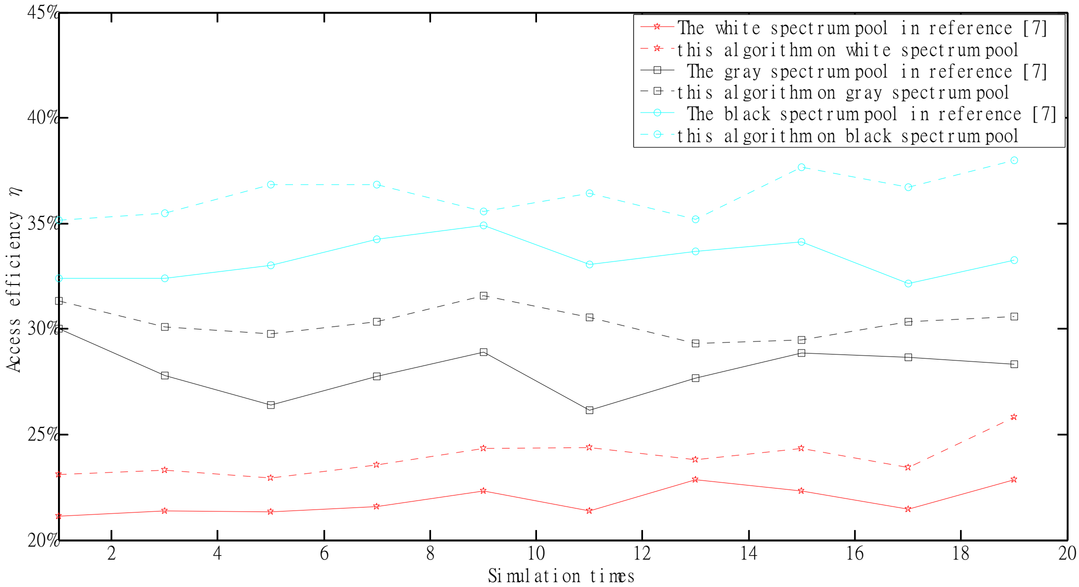

Fig. 5. Comparison of the access efficiency for different number of users

In order to verify the advantages of the improved multi-objective clustering algorithm, in this paper, three sets of data are randomly generated, and each set contain 200 data. These data are clustered by the algorithm of this paper and the existing multi-objective algorithm. The simulation results are shown in Fig. 6 and Fig. 7. It can be seen from the comparison diagram that, by introducing the principle of granularity, the compactness of cluster of the algorithm in this paper is better, and the separation between clusters is better than the existing multi-objective algorithm. The feasibility of the algorithm is fully proved.

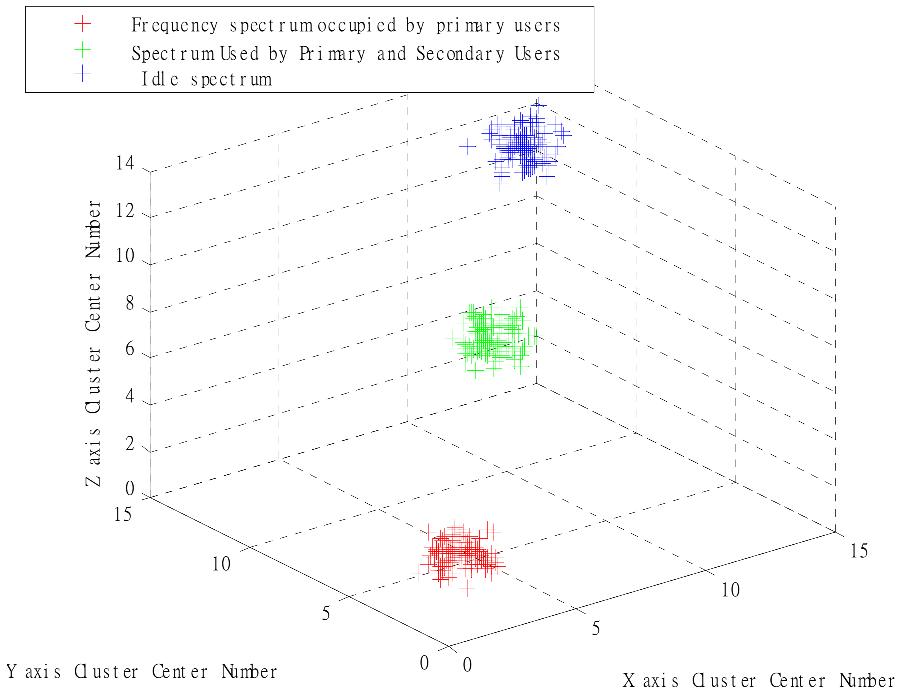

Fig. 6. Spectrum pool clustering results of this algorithm

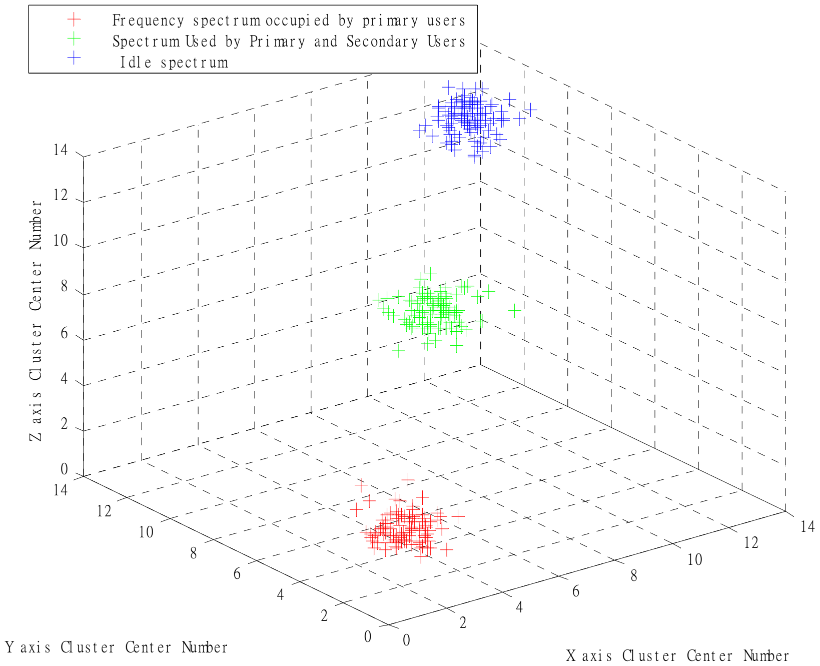

Fig. 7. Spectrum pool clustering result of multi-objective clustering algorithm

Fig. 8 shows the convergence speed of the algorithm for different user numbers. The average number of iterations of the improved algorithm in this paper is better than the existing multi-objective clustering algorithm. When the spectrum information is known, the algorithm can converge faster, save time and reduce system delay effectively.

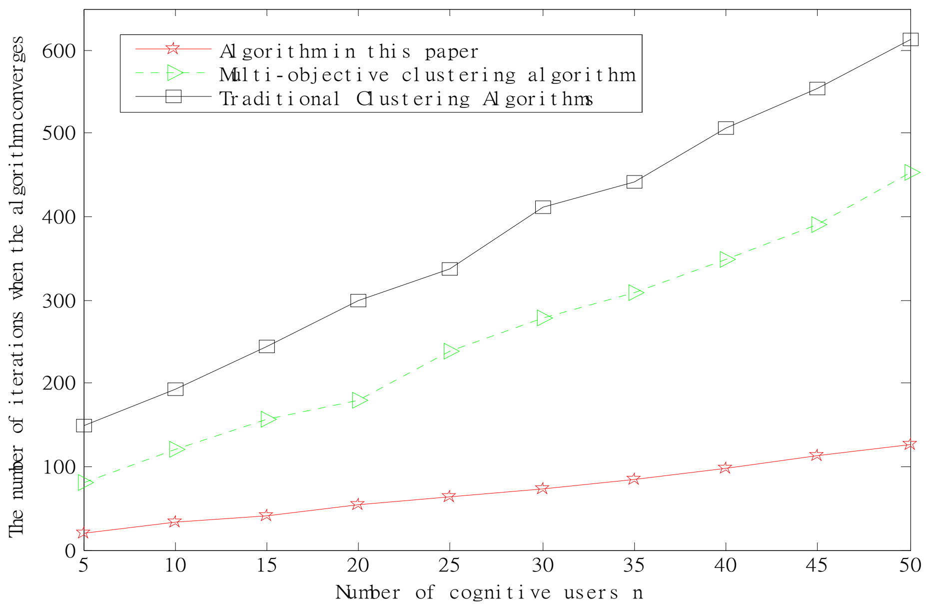

Fig. 8. The number of iterations when the algorithm converges

5 Conclusion

In this paper, sub-channels are clustered by cognitive user's different service requirements (interference, delay, throughput, bit error rate). In this algorithm, we firstly establish a multi-objective matrix model and use the multiple target parameters to describe the channel characteristics of the primary user. It improves the accuracy of spectrum clustering and makes the cognitive users channel access more reliable. Then, different cognitive users access a more efficient channel according to different characteristics, which improves the overall level of the system. Based on the C-means clustering algorithm in this paper, we will further improve the clustering process and increase the spectrum access speed by combining with the energy detection algorithm.

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