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Cognitive Radio Technology using Multi Armed Bandit Access Scheme in WSN

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Abstract: *A major challenge in CR-WSN is utilizing spectrum more efficiently. Therefore, a novel channel access scheme is proposed for the problem that how to access the multiple channels with the unknown environment information for cognitive users, so as to maximize system throughput. In order to solve the competition and the fairness between cognitive users of WSNs, a fair channel-grouping scheme is proposed. The proposed scheme divides these channels into M groups according to the water filling principle based on the learning algorithm UCB-K index. Finally, the experimental results demonstrate that the proposed scheme cannot only effectively solve the problem of collision between the cognitive users, improve the utilization rate of the idle spectrum, and at the same time reflect the fairness of selecting channels between cognitive users.*
Keywords: *multi-armed bandit, fairness access scheme, channel-grouping, modi ed UCB-tuned.*

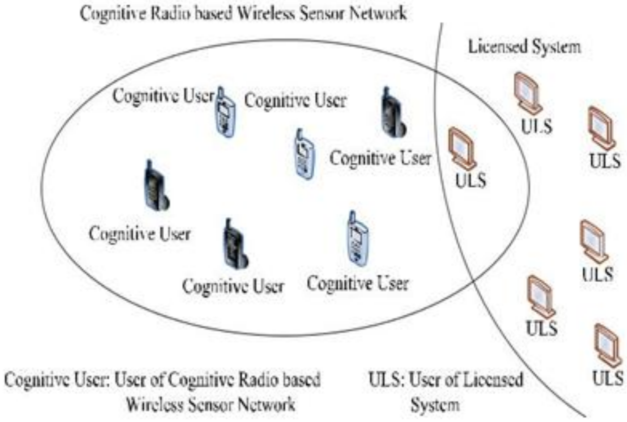
I. Introduction

Spectrum Accessing

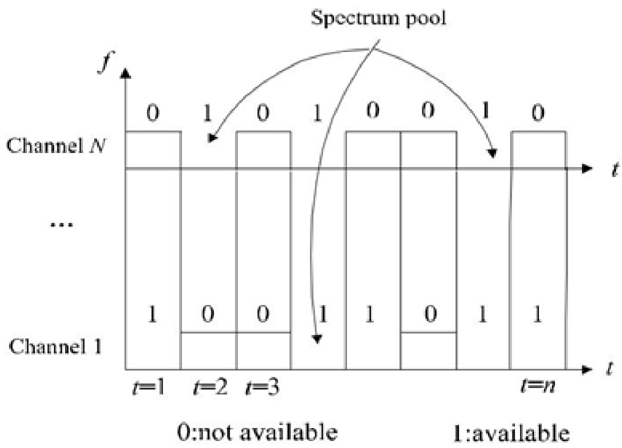
Today's radio spectrum is very crowded for rapid increasing popularities of various wireless applications. Therefore, cognitive radio technology stands as a key and spectrum-efficient communication approach for resource-constrained wireless sensor networks and future wireless network [24] [26]. when cognitive users, namely, sensor nodes in wireless sensor networks access the spectrum competitively, in order to make effective usage of the spectrum and meet the throughput demand for multimedia applications, effective mechanisms are required to coordinate cognitive users' behaviors (transmission power control, spectrum access, et al.) [27] [35]. at the same time, the wireless environment is gradually to be more complicated, which makes it more difficult for cognitive users to obtain the complete network environment parameters information in the wireless network system. also, the upcoming 5g networking architectures with a super high spectrum utilization and ultra-low power consumption, tends to support massive devices. Most of the current literatures, such as [47] and [48] are limited that one cognitive user can only select one channel each time. we propose a scheme which is based on channel grouping. In each time slot, cognitive users can sense all of the channels in the group one by one, until ending an idle channel or all of the channels are perceived once. Here, these channels are divided into several groups according to the water filling principle based on the modified UCB-tuned index. On the other hand, many literatures don't take the fairness among the cognitive users into consideration. In this paper, we introduce the fairness access scheme based on the channel grouping method. Finally, the experimental results show that the pro-posed scheme can get a logarithmic regret with respect to time slot, and increase the selected number of the channels that has a small idle probability, so as to ensure the fairness among the cognitive users.

II. System Model

A CR-WSN coexisting with a licensed system is considered. The time is slotted and the N channels are independent of each other.



The mean of random variable X_i .n/ is $_i$ D E[X_i], where we normalize X_i 2 [0; 1]. Different channels have different means $_i$, which is unknown for these cognitive users and there is no information exchange or communication between cognitive users. In the distributed CR-WSN, each cognitive user can select one opportunity channel from the *N* channels. The channel set is *N* , f1; : : : ; *N* g. These channels are divided into time slots one by one.



As shown in Fig 2, each channel has two states: $s_i(n)$ D 1 and $s_i(n)$ D 0. $s_i(n)$ D 1 represents that in each time slot, the channel is not occupied by the licensed user (i.e. the channel is available), otherwise, $s_i(n)$ D 0 (i.e. the channel is not available). The set of the channels state space is *S* D f$s_1(n)$; $s_2(n)$; : : : ; $s_i(n)$: : : ; $s_N(n)$g. For cognitive user *i*, the closed-form normalized instantaneous reward at slot *n* is $X_i(n)$ D $s_i(n)$ *B*; X_i 2 [0; 1]. Here let *B* D 1. These channels are independent and identically distributed with different Bernoulli parameters. The objective function is to maximize the total throughput or minimize the regret. So we formulate the problem as I.I.D. MAB model. In the model, cognitive users do not know the channel state information, and they have to estimate and predict channel availability by exploring and learning. The scheme performance is evaluated by its regret value, which means that the difference between the obtained reward under an ideal environment and the obtained practical reward by taking some strategies.

III. The Principle Of The Proposed Scheme

A. Distributed learning algorithm based on modified UCB-tuned index

Due to the channel environment statistical information is completely unknown to cognitive users, we need to predict he channel information by learning algorithm. The proposed distributed learning algorithm in this paper is briefly called CBT-K that modified based on the tuned upper confidence bound (UCBT) index, which introduces a variance factor in the index and it is generalized form of the modified UCBT. The UCBT-K can select arbitrarily channel with the K-th largest index value. The process of UCBT-K on *M* cognitive users can be obtained as follows.

Initialization: Cognitive user *m* senses all the channels one by one.

$$T_i(t) = 1.$$

Channel Estimation: Calculate the improved CB-tuned index for each channel according to the mathematical formula

$$\hat{\mu}_{m,i}(t-1)+\sqrt{\frac{\log(t)}{T_i(t-1)}} \times\sqrt{\min\left(\frac{1}{4},\delta_i^2(t-1)+\sqrt{2\log n/T_i(t-1)}\right)} \quad (4)$$

Channel Selection: Select a channel k from oK based n the following mathematical formula

$$k=\arg\min_{i\in o_K}\hat{\mu}_{m,i}(t-1)+\sqrt{\frac{\log(t)}{T_i(t-1)}} \times\sqrt{\min\left(\frac{1}{4},\delta_i^2(t-1)+\sqrt{2\log(t)/T_i(t-1)}\right)} \quad (5)$$

Update Information: if the selected channel is idle, pdate the average reward

$$\hat{\mu}_{m,k}(t)=\frac{\hat{\mu}_{m,k}(t-1)\times T_k(t-1)+X_k(t)}{T_k(t-1)+1} \quad (6)$$

B. The principle of channels grouping

There are M distributed cognitive users and N channels in the system ($M < N$). The principle of channel grouping can be shown as the following

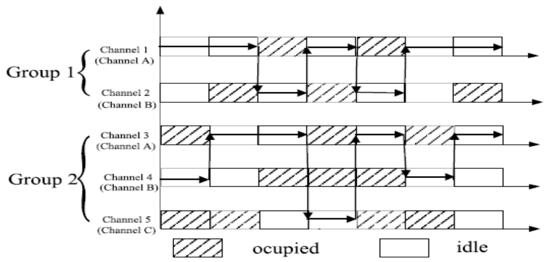


FIGURE 3. The channel sensing based on channel group.

Assume that the time lot consists of three parts: the detection, the access process and the decision. We assume the first part and the third part s quite short and can be ignored. In this article we allow cognitive user to sense more than one channel in a time lot.

Firstly, we let the channel with the largest index value in the set o_M as the channel A of the first channel-group (G_1 D fAg). Assume that the time lot consists of three parts: the detection, the access process and the decision. We assume the first part and the third part s quite short and can be ignored. In this article we allow cognitive user to sense more than one channel in a time lot.

c. The access of channel-groups with fairness

Since there are multiple cognitive users in the system, it is ecessary to end a reasonable channel access scheme to void collisions among cognitive users. In literature , the priority access scheme is adopted to avoid collisions. First, it assigns a rank of priority access for each cognitive user. Then each cognitive user chooses the corresponding channel according to its rank. For example, for cognitive user 1 its priority is the first, so it can choose the channel with largest index value every time. In term of the cognitive user 2, its priority is the second, it will always select the one with second largest index value. And the other cognitive users select in the same way. As a result, each cognitive user has a corresponding channel. Although this scheme can effectively void the collision among cognitive users, it does not reflect he fairness among cognitive users. Therefore, to solve the problem of unfairness, we propose an access scheme which s based on channel grouping, as shown in Fig. 4.

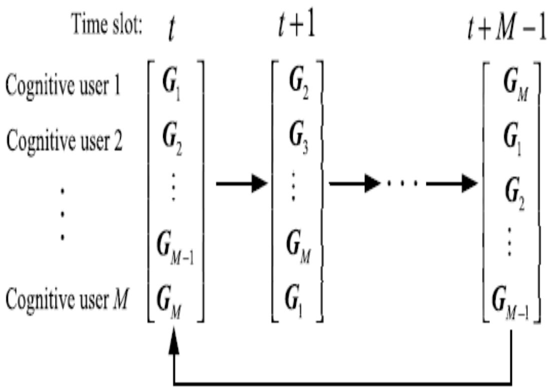


FIGURE 4. Channel-group access scheme with fairness.

$$G_j = ((m+t) \bmod M) + 1 \qquad (7)$$

The algorithm implementation of the proposed scheme can be shown in Fig. 5, which includes three parts: distributed learning, channel grouping and fair access scheme.

$$\Pr\left\{\hat{\mu}_{j(t),n_{j(t)}} \le \mu_{j(t)} - C_{t,n_{j(t)}}\right\} \le t^{-4} \qquad (8)$$

$$\Pr\left\{\hat{\mu}_{i,n_i} \ge \mu_i + C_{t,n_i}\right\} \le t^{-4} \qquad (9)$$

$$\hat{\mu}_{j(t),Q^m_{j(t)}(t-1)} + C_{t-1,Q^m_{j(t)}}(t-1) \le \hat{\mu}_{i,Q^m_i(t-1)} + C_{t-1,Q^m_{i(t)}}(t-1) \qquad (10)$$

$$\begin{aligned} Q_i^m(n) &= 1 + \sum_{t=N+1}^{n} \| \{I_i(t)\} \le l \\ &\quad + \sum_{t=N+1}^{n} \| \{I_i(t), Q_i^m(t-1) \ge l\} \\ &\le l + \sum_{t=N+1}^{n} \begin{pmatrix} \| \{I_i(t), \mu_i < \mu_{K_m^*}, Q_i^m(t-1) \ge l\} \\ + \| \{I_i(t), \mu_i > \mu_{K_m^*}, Q_i^m(t-1) \ge l\} \end{pmatrix} \end{aligned} \qquad (11)$$

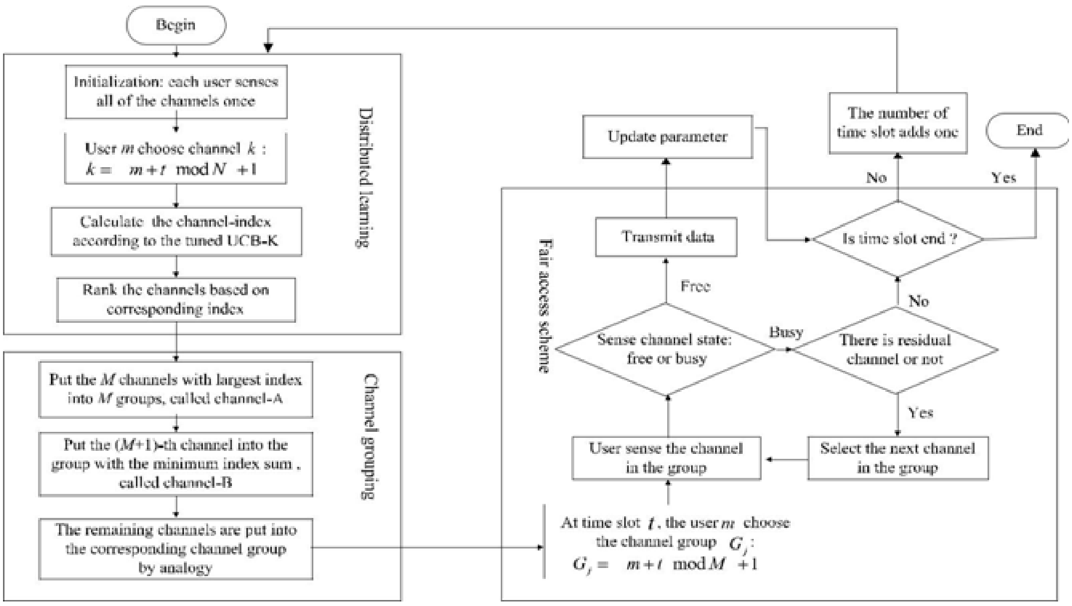
$$\le \sum_{t=1}^{\infty}\sum_{n_{j(t)}=1}^{t-1}\sum_{n_i=l}^{t-1} 1\{\hat{\mu}_{j(t),n_{j(t)}} + C_{t,n_{j(t)}} \le \hat{\mu}_{i,n_i} + C_{t,n_i}\} \quad (12)$$

$$\mu_{j(t)} < \mu_i + 2C_{t,n_i} \quad (13)$$

$$\hat{\mu}_{j(t),n_{j(t)}} \le \mu_{j(t)} - C_{t,n_{j(t)}} \quad (14)$$

$$\hat{\mu}_{i,n_i} \ge \mu_i + C_{t,n_i} \quad (15)$$

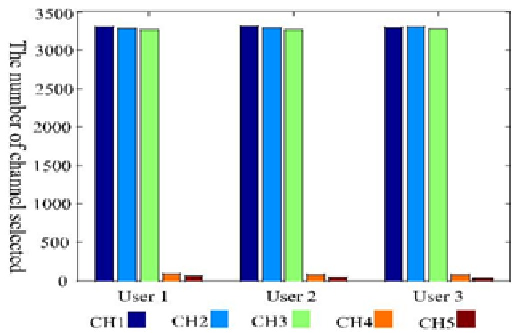
$$\begin{aligned} &\mu_{j(t)} - \mu_i - 2C_{t,n_i} \\ &\ge \mu_{K_m^*} - \mu_i - 2\sqrt{\frac{2\Delta^2_{K_m^*,i}\ln t}{8\ln n}} \\ &\ge \mu_{K_m^*} - \mu_i - \Delta_{K_m^*,i} = 0 \end{aligned} \quad (16)$$



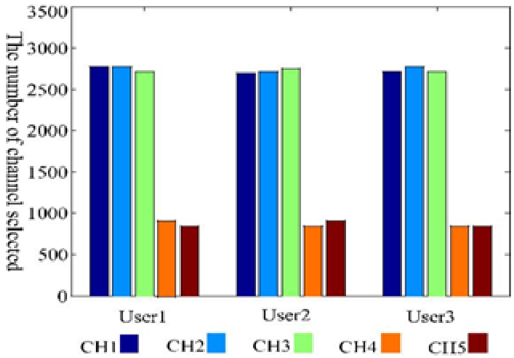
IV. Simulation And Analysis

A. The complexity analysis of regret

According to the conclusion of Theorem 1, when n=ln n C, (C is a constant which is related to cognitive users and channels, C D 8 .N C M /=$1^2_{\min}$ C 1 C 2 ^{2}=3 N C M).



we can end the fairness between different cognitive users has been reflected, but the usage of the channels with smaller idle probability is low, such as channel *i* D 4 and *i* D 5. In Fig. 9, the proposed scheme not only reflects the fairness between various cognitive users, but also takes more advantages of channels with smaller idle probability. By fairness of channels selection, all the channels are selected more times, which can avoid the situation that only one or a small number of channels are selected while most of the others are unselected. The more channels are selected, the more opportunities for cognitive users to access channels, therefore, the efficiency of channel usage is improved.



V. Conclusion

In this paper, a multiple cognitive users and multiple channels system is considered in CR-WSNs. The channels statistical information is completely unknown for the cognitive users. To solve the problem of channel selection in CR-WSNs, a novel fair access scheme with channel grouping is proposed. Firstly, an online learning method called modi ed UCB-K based on the well-known UCB is used. Then these channels are divided into several groups according to the principle of channel grouping, which can improve the usage rate of the idle spectrum. Besides, we adopted the distributed learning with fairness to avoid collision between cognitive users and at the same time embody the fairness between cognitive users. Finally, the simulation results also show the superiority of the proposed scheme. With the development of the Internet of Things, the scale of networks is larger and larger. How to obtain and deal with the large amount of channel information for larger scale wireless sensor networks may be a promising research topic, and schemes based on wireless big data may be adopted.

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