Energy-Efficient Spectrum Sensing for CRSNs via Optimization of Sensing Time

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Abstract

In cognitive radio sensor networks (CRSNs), secondary users (SUs) can occupy licensed bands opportunistically without causing interferences to primary users (PUs). SUs perform spectrum sensing to detect PUs are present or not. Sensing time is a critical parameter for spectrum sensing. It can yield a tradeoff between sensing performance and secondary throughput. In this paper, we propose an energy-efficient spectrum sensing scheme for CRSNs. In our proposed scheme, SU will dynamically decide to perform spectrum sensing one or two periods according to the sensing result of the current frame. Because of energy constraint in CRSNs, the network energy efficiency is maximized via optimization of sensing time. Simulation results show that our proposed scheme can obtain a better performance in terms of energy efficiency. Simultaneously, PU can be provided a better protection.

Key words: Cognitive radio sensor network, sensing time, energy efficiency, miss detection probability.

1. Introduction

Cognitive radio (CR) technology is applied to improve spectral efficiency. Spectrum sensing is performed by secondary users (SUs) to search the *spectrum hole* or *white space*. In terms of spectrum sensing, the effect of sensing time on spectrum sensing performance is significant. It can yield a tradeoff between sensing performance and secondary throughput.

There are many works on the optimization of sensing time. A scheme for joint optimization of channel sensing time and channel sensing order is proposed in [1]. The optimization problem is formulated to find optimal sensing time which can maximize the secondary throughput. Hao *et al.* [2] develop a novel adaptive spectrum sensing scheme to improve the average throughput reward. The spectrum sensing duration can be adjusted according to the previous sensing results and channel state information. In [3], authors propose a learning-based spectrum sensing time optimization scheme to maximize the average throughput of the cognitive radio system. By optimizing spectrum sensing time, the objective that maximizing the average throughput of a cognitive radio system is achieved. However, these above-mentioned technologies specific to cognitive radio networks (CRNs) cannot be directly applied in CRSNs, because they do not consider energy restriction. In CRSNs, wireless sensor devices powered by batteries have to suffer the energy constraint. This makes energy-efficient design be the essential consideration for CRSNs.

Inspired by previous works, we propose an energy-efficient spectrum sensing scheme for CRSNs. The individual spectrum sensing is performed by a single SU. In the proposed scheme, SU can dynamically decide to sense the spectrum one or two periods according to the sensing result of the current frame. The energy efficiency can be maximized by the optimization of sensing time. Furthermore, through a set of simulations, it is verified that a better performance can be achieved in terms of network energy efficiency by our proposed scheme.

The rest of the paper is organized as follows. We propose our scheme with mathematical analysis in Section 2. The performance of the proposed scheme is evaluated by a set of simulations in Section 3. Finally, Section 4 concludes this paper.

2. Proposed scheme

In proposed scheme, time is assumed to be divided into equal frame. Each frame contains sensing phase and data transmission phase. In this paper, we prefer to provide a better protection for PU. SU performs spectrum sensing one time and then wait for the next frame if PU is detected to be present. If sensing result shows PU is idle, SU will perform spectrum sensing again to verify the absence of PU. If sensing result still shows PU is absent, data will be transmitted. Therefore, according to the proposed spectrum sensing scheme, 6 cases can be listed as below. d_0 and d_1 denote sensing results corresponding to the absence and presence of PU, respectively.

S1: PU is actually present, and sensing result is d_1.

S2: PU is actually present, and the first and the second sensing results are d_0 and d_1, respectively.

S3: PU is actually present, while both of the first and the second sensing results are d_0.

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S4: PU is actually absent, while the sensing result is d_1.

S5: PU is actually absent, and both of the first and the second sensing results are d_0.

S6: PU is actually absent, and the first and the second sensing results are d_0 and d_1, respectively.

In CRSNs, a binary hypothesis testing problem is utilized to formulate spectrum sensing as follows:

$$\mathcal{H}_0\colon\ y(n) = u(n), \tag{1}$$

$$\mathcal{H}_1\colon\ y(n) = x(n) + u(n), \tag{2}$$

where hypothesis $\mathcal{H}_0$ and $\mathcal{H}_1$ indicate that PU is absent and present, respectively. p_0 and p_1 are the probabilities of $\mathcal{H}_0$ and $\mathcal{H}_1$, respectively. The noise $u(n)$ is assumed to be an iid Gaussian random process with zero mean and variance σ_y^2. And the received PU's signal $x(n)$ is an iid random process with mean zero and variance σ_x^2.

In this paper, we employ energy detector as the spectrum sensing scheme. The test statistic can be calculated as below:

$$\mathrm{T}(\mathrm{y}) = \sum_{n=1}^{N} \left| y(n) \right|^2, \tag{3}$$

where N is the number of sample times. The test statistic follows the central and non-central chi-square distribution with $2N$ degrees of freedom under hypothesis $\mathcal{H}_0$ and $\mathcal{H}_1$, respectively. The test statistic can be approximated as Gaussian, because central limit theorem can be utilized for it if N is large.

$$\mathrm{T}(\mathrm{y}) \sim \begin{cases} \mathcal{N}(N, 2N), & \mathcal{H}_0 \\ \mathcal{N}\left(N(1+\gamma), 2N(1+\gamma)^2\right), & \mathcal{H}_1 \end{cases}, \tag{4}$$

where $\gamma = \sigma_x^2/\sigma_y^2$ is the signal to noise ratio received from PU. We can get the detection probability p_d and the false alarm probability p_f based on the statistics of $\mathrm{T}(\mathrm{y})$.

$$\begin{aligned} p_d &= p\left(\mathrm{T}(y) > \lambda \mid \mathcal{H}_1\right) \\ &= \mathcal{Q}\left(\frac{\lambda}{\sqrt{2N}(\gamma+1)} - \sqrt{\frac{N}{2}}\right), \end{aligned} \tag{5}$$

$$\begin{aligned} p_f &= p(\mathrm{T}(y) > \lambda \mid \mathcal{H}_0) \\ &= \mathcal{Q}\left(\frac{\lambda}{\sqrt{2N}} - \sqrt{\frac{N}{2}}\right), \end{aligned} \tag{6}$$

where λ is the sensing threshold, and $\mathcal{Q}(\cdot)$ is Q function. If the received power is bigger than threshold λ, we consider that PU is present; otherwise, we consider PU is absent. The function of λ can be derived by Eq. (5) as

$$\lambda = \sqrt{2N}(1+\gamma)\left(Q^{-1}(p_d) + \sqrt{\frac{N}{2}}\right), \tag{7}$$

where $\mathcal{Q}^{-1}(\cdot)$ denotes the inverse function of Q function. Eq. (7) is substituted into Eq. (6) and we can get:

$$p_f = Q\left((1+\gamma)Q^{-1}(p_d) + \gamma\sqrt{\frac{N}{2}}\right). \tag{8}$$

In this paper, in order to guarantee the essential requirement of CRSNs, the false alarm threshold p_f^{th} and the detection probability threshold p_d^{th} are also set for SUs. Because Q function is the monotone decreasing function, in order to maximize the secondary throughput, we make $p_d = p_d^{th}$. And according to above-mentioned 6 cases, it is known that S3 can lead to the problem of miss detection. So miss detection probability p_m can be expressed as

$$p_m = p_1(1-p_d)^2. \tag{9}$$

And then, according to above 6 cases, the optimization model is established as below.

Based on 6 cases, it is known that throughput is achieved by S5. Therefore, the average throughput can be expressed as

$$R(\tau) = p_0(1-p_f)^2 (T-2\tau)C, \tag{10}$$

where T is the length of frame, τ denotes sensing time. C is the data transmission rate of SU. And energy consumption functions corresponding to 6 cases can be formulated as below.

$$E_1 = p_1 p_d E_s \tau, \tag{11}$$

$$E_2 = 2p_1(1-p_d)\, p_d E_s \tau, \tag{12}$$

$$E_3 = p_1(1-p_d)^2 \left(2E_s\tau + E_t(T-2\tau)\right), \tag{13}$$

$$E_4 = p_0 p_f E_s \tau, \tag{14}$$

$$E_5 = p_0(1-p_f)^2 \left(2E_s\tau + E_t(T-2\tau)\right), \tag{15}$$

$$E_6 = 2p_0(1-p_f)\, p_f E_s \tau, \tag{16}$$

$$E_{total} = E_1 + E_2 + E_3 + E_4 + E_5 + E_6, \tag{17}$$

where E_1, E_2, E_3, E_4, E_5, and E_6 represent the energy consumption of S1, S2, S3, S4, S5, and S6, respectively. E_{total} is the average of the total energy consumption. E_s and E_t denote energy consumption of spectrum sensing and data transmission for unit time. In this paper, the definition of energy efficiency in [4] is used. Therefore the objective function of energy efficiency can be expressed as

$$\begin{aligned} &\psi(\tau) = \frac{R(\tau)}{E_{total}}, \\ &s.\ t.\ \ p_f \le p_f^{th}. \end{aligned} \tag{18}$$

The value of τ which can maximize ψ is the optimal spectrum sensing time. The exhaustive search method is utilized to figure out the maximum value of ψ.

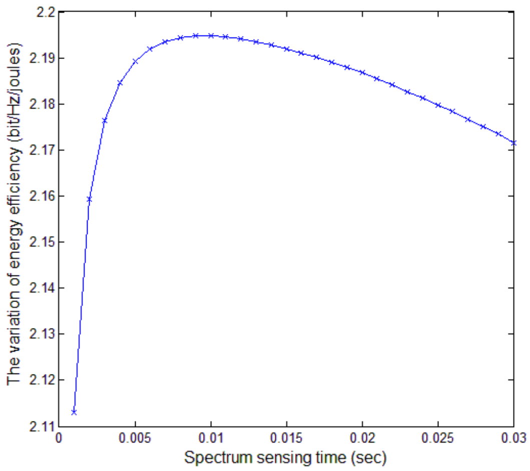

Fig. 1 The variation of energy efficiency with increasing spectrum sensing time

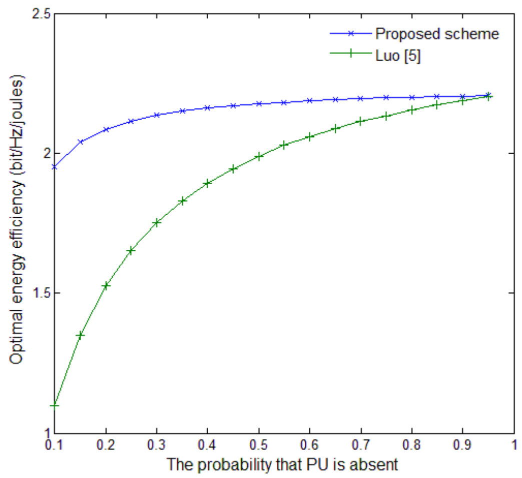

Fig. 2 Comparison of optimal energy efficiency

3. Performance evaluation

In this Section, we show the performance of the proposed scheme, and compare it with the scheme proposed in [5]. The simulation for the performance evaluation is implemented with MATLAB. In order to evaluate the performance of the proposed scheme, simulation parameters are set as below. A CRSN which consists of one PU and 10 SUs is assumed. *C*=6.6582*bit/sec/Hz*, $p_d^{th} = 0.9$, $p_f^{th} = 0.1$, *T*=0.2*s*, $E_s = 0.1W$, $E_t = 3W$, $\gamma = -20dB$.

Fig. 1 shows the energy efficiency variation of SU with the increasing sensing time when $p_0 = 0.7$ is given. From Fig. 1, we can get that the energy efficiency of SU will increase with the increasing sensing time at first. And then after the optimal point, it decreases again. The reason is that false alarm probability is decreased with increasing sensing time, and this implies that more opportunities of spectrum hole can be utilized by SU, and more throughputs can be achieved. However, due to the fixed frame time *T*, data transmission time will be decreased with the increasing sensing time. It will affect the throughput of SU when sensing time is large. That is why energy efficiency of SU is decreased again. Fig. 1 also confirms that the optimal sensing time which can maximize the energy efficiency of the secondary network exactly exists.

The proposed scheme is also compared with the minimizing mean detection time scheme proposed by Luo *et al.* [5]. According to Fig. 2, we can get that the optimal energy efficiency of the proposed scheme is always higher than Luo [5]. The reason is that the miss detection of our proposed scheme is lower. According to Eq. (9), we can get that p_m is $(1 - p_d)$ times of the miss detection probability in Luo [5]. In this paper, because p_d is fixed as 0.9, the miss detection probability can be decreased by ten times with our proposed scheme. Even though we spend more time to detect PU when sensing result is d_0, due to the lower miss detection probability, PU can be protected better. More invalid data transmission can be avoided, and more unnecessary energy consumption can be saved. In this way, the network energy efficiency can be promoted.

4. Conclusion

In this paper, we proposed a novel spectrum sensing scheme for CRSNs, and the network energy efficiency is maximized by the optimization of sensing time. According to the sensing result of the current frame, SU can dynamically decide to perform spectrum sensing one or two times. In order to provide a better protection for PU, SU will detect PU again to confirm the absence of PU when sensing result shows that PU is absent. Finally, a set of simulations validate that the proposed scheme has a better performance in terms of energy efficiency. In addition, benefit from the lower miss detection probability, PU can obtain a better protection.

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