Bayesian Energy Detection Based on Temporal Persistence

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Abstract. Energy detection is one of the classical methods for spectrum sensing in Cognitive radio (CR). Previous research on energy detection is almost based on single time slot, while the communication process of the primary user (PU) is hardly completed in one time slot. In this study, the authors consider 2-slot temporal persistence (TP) that PU maintains the same state (absence or presence) for at least 2 slots. Since we cannot know the actual state of PU in spectrum sensing, two kinds of TP results are obtained, based on which an improved TP-based Bayesian Energy Detection (ITPBED) is proposed. Simulation results show that, compared with TPBED, ITPBED scheme can achieve significant reduction in false alarm probability, missed detection probability and Bayesian cost when signal-to-noise ratio (SNR) is less than -10 dB; in other SNR regions, the performance of ITPBED scheme is also superior to Bayesian Energy Detection (BED) scheme.

Introduction

In recent years, with the development of wireless communication technology, the majority of spectrum resource has been allocated for specific use. According to the spectrum report published in 2010 by The Federal Communications Commission (FCC) [1], the available spectrum resources are on the verge of extinction. However, many researchers analyze and monitor the use of radio spectrum, finding that significant amount of spectrum remains underutilized, and even completely idle [2]. In order to solve this problem, authors in [3, 4] put forward secondary market of spectrum to improve the spectral efficiency, in which context cognitive radio (CR) was proposed by Mitola and Maguire [5].

CR is a promising solution to the spectrum scarcity issue [6] via enabling the secondary user (SU) to take chances to access the unutilized spectrum without causing interference to the primary user (PU). Consequently, SU has to continuously and reliably detect whether PU is present or not. There are three classical spectrum sensing (SS) technologies, matched filter detection [7], cyclostationary feature detection [8] and energy detection (ED) [9]. Among them, ED is found to be the simplest and the most widely used SS mechanism since it does not require prior information about PU signals. ED senses the presence of PU signal by accumulating the energy of the received signal over a specific time interval [10]. There exist many drawbacks for ED, the threshold highly depends on the environment conditions [11], robustness is poor and the estimation error due to noise may degrades sensing performance significantly at low signal-to-noise ratio (SNR) values [10, 12].

In [13], the authors propose the concept of PU's temporal persistence (TP) and prove that the prediction probabilities of PU's state are at least not worse than the prior probabilities when considering TP. The concept of TP derived from the research of target recognition in the field of image processing. In practice, PU can hardly complete its communication process in a single slot, which means that if PU becomes present in a slot to begin communicating, it will probably keep present in the next slot. Using the characteristic of TP to adjust the decision threshold, they propose TP-based Bayesian Energy Detection (TPBED) scheme.

This paper considers the 2-slot TP that PU maintains the same state (absence or presence) for at least 2 slots. Based on TP's characteristic and detection results of previous 2 slots, we can get a TP result rather than adjust the decision threshold. When detection results are '01' or '10', We consider TP result instead of performing BED to reduce the false alarm probability, missed detection probability and Bayesian cost in current slot. Detection results of '01' denote PU's absence in the

(i-2)th slot and presence in the (i-1)th slot and '10' denote PU's presence in the (i-2)th slot and absence in the (i-1)th slot.

System Model

In SS, in order to continually sense the state of PU, SU performs ED in each slot, which is regarded as a binary hypothesis problem as follows:

$$y(t)=\begin{cases} n(t) & H_0 \\ s(t)+n(t) & H_1 \end{cases}. \tag{1}$$

where the y(t) is the received signal at the SU; n(t) denotes the additive white Gaussian noise (AWGN) with zero mean and unit variance; s(t) denotes PU signal with unit power; H0 and H1 denote absence and presence of PU, respectively. In this case, the energy statistic is given as

$$v_i=\sum_{k=1}^{M}\left|y_i(k)\right|^2. \tag{2}$$

where v_i denotes the received energy in the ith slot, M means the sampling number.

Since M is usually very large, v_i approximately obeys Gaussian distribution according to the center limit theorem (CLT) [14, 15], and false alarm probability P_f and missed detection probability P_m are given as follows:

$$P_f=\int_{\lambda}^{\infty} f\left(v_i\left|H_0\right.\right)dv_i=Q\left(\frac{\lambda-M}{\sqrt{2M}}\right). \tag{3}$$

$$P_m=\int_{-\infty}^{\lambda} f\left(v_i\left|H_1\right.\right)dv_i=1-Q\left(\frac{\lambda-M\left(1+\gamma\right)}{\sqrt{2M\left(1+2\gamma\right)}}\right). \tag{4}$$

where λ is the threshold to decide whether PU is present or not; γ is the received SNR measured by SU; Q(·) is the Q-function.

Most of the ED adopts constant false-alarm criterion to determine the threshold, and there is no limit on missed detection probability. In order to jointly consider the false alarm probability and missed detection probability, BED that uses Bayesian cost to determine the optimal threshold is investigated. The definition of Bayesian cost can be expressed as [15]

$$J=I_f P_0 P_f+I_m P_1 P_m. \tag{5}$$

where I_f and I_m are the impact factor of false alarm and missed detection, respectively; P_0 and P_1 are the prior probability of hypothesis H_0 and H_1, respectively.

In [13], the authors minimize the Bayesian cost and obtain the optimal threshold

$$\lambda^{BED}=\frac{M}{2}+\sqrt{B\left[A-\ln\left(\frac{P_1}{P_0}\right)-\ln\left(\frac{I_m}{I_f}\right)\right]}. \tag{6}$$

Where $A=M\cdot\gamma/8+\left[\ln\left(1+2\gamma\right)\right]/2, B=\left[2M\left(1+2\gamma\right)\right]/\gamma$.

In this case, (3) and (4) can be rewritten as

$$P_f = Q\left(\sqrt{\frac{1+2\gamma}{\gamma}\left[A-\ln\left(\frac{P_1}{P_0}\right)-\ln\left(\frac{I_m}{I_f}\right)\right]}-\frac{\sqrt{2M}}{4}\right). \tag{7}$$

$$P_m = 1-Q\left(\sqrt{\frac{1}{\gamma}\left[A-\ln\left(\frac{P_1}{P_0}\right)-\ln\left(\frac{I_m}{I_f}\right)\right]}-\frac{\sqrt{2M\left(1+2\gamma\right)}}{4}\right). \tag{8}$$

ITPBED scheme

As discussed above, PU has the characteristic of TP that PU maintains the same state (absence or presence). In this section, we will propose ITPBED scheme.

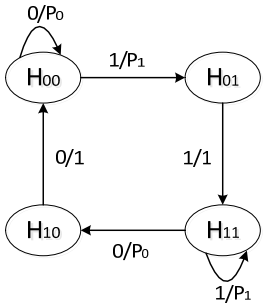

Fig. 1. State transition diagram of PU's states

In the ith slot, we assume that PU's actual states in the previous two slots are H_{00}, H_{01}, H_{10} and H_{11}. Among them, H_{00} and H_{11} denote PU's continuous absence and continuous presence, respectively; H_{01} denotes that PU is absent in the (i-2)th slot and present in the (i-1)th slot; H_{10} denotes PU's presence in the (i-2)th slot and absence in the (i-1)th slot. Since PU maintains the same state for at least 2 slots, when PU's state is H_{01}, PU will maintain presence in the ith slot; similarly, when H_{10}, PU will maintain absence in the ith slot. We can draw the state transition diagram in the previous two slots, as shown in Fig. 1. Without loss of generality, we assume $P_0 = P_1 = 1/2$ in this paper. According to this Markov chain, we can calculate the steady probability of each PU's actual states $P(H_{00}) = P(H_{11}) = 1/3$, $P(H_{01}) = P(H_{10}) = 1/6$.

But in the process of spectrum sensing, we cannot know the actual state of PU, hence, we consider using detection results of PU in the previous two slots to replace actual states. In [13], the authors prove that when detection results are '01' or '10' in the previous two slots, the current state is probably high probability of '1' or '0', respectively.

In this paper, we propose ITPBED scheme which simply considers TP result, that is, if detection results of PU in the previous two slots are '01' or '10', we believe that PU is present or absent in current slot, respectively. To be specific, when detection results are '01', we consider that PU is present in current slot without performing BED; when detection results are '10', we consider that PU is absent in current slot without performing BED; when others, the process is the same to BED.

The detailed steps of ITPBED scheme can be found below.

Step 1: Initialization. Perform detection according to BED scheme in the first 2 slots, and store the results; i = 3.

Step 2: Comparing the detection result of i-2 and i-1 slot. When they are different, go to Step 4.

Step 3: Perform BED; go to step 5.

Step 4: When the results are '01' / '10', the result of i slot is '1' / '0', respectively.

Step 5: Store the result in i slot; i = i + 1; go to Step 2.

Simulation results

In this section, we will present some simulation results to demonstrate the validity of our proposed ITPBED scheme. Results are obtained using Monte Carlo simulations of 100000 runs, and the sampling number is 500.

The false alarm probabilities of BED scheme, TPBED scheme and ITPBED scheme versus SNR are given in Fig. 2, respectively. Fig. 3 shows the missed detection probabilities of three schemes versus SNR, respectively. We come to the same conclusion from these two figures, when $SNR < -10dB$ the curve of ITPBED is lowest and when $SNR > -10dB$ the curve of TPBED become lowest, which illustrates that ITPBED scheme and TPBED scheme are superior to BED scheme, and ITPBED scheme is the best scheme when $SNR < -10dB$, in terms of false alarm probability and missed detection probability.

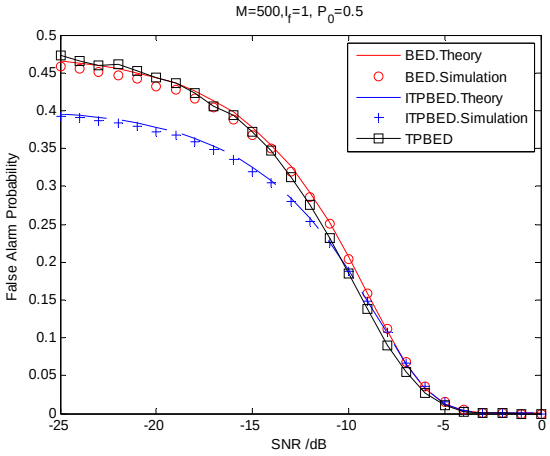

Fig. 2. False alarm probabilities of three schemes against SNR

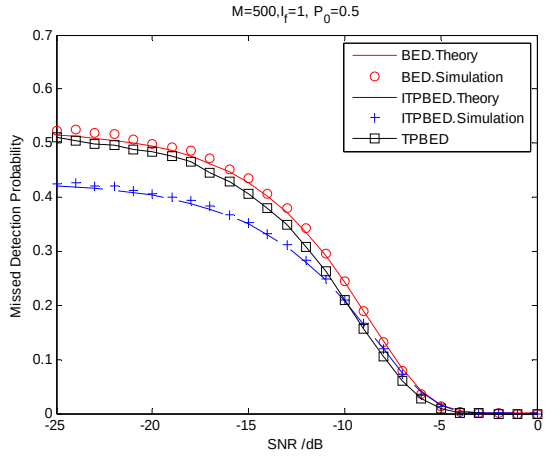

Fig. 3. Missed detection probabilities of three schemes against SNR

Fig. 4 indicates the Bayesian costs of three schemes versus SNR, respectively. Similarly, when $SNR < -10dB$, Bayesian cost curve of ITPBED scheme is lower to the curve of TPBED, which means that global performance of ITPBED scheme is superior to TPBED scheme and when $SNR > -10dB$, global performance of ITPBED scheme is not better than TPBED scheme, but superior to BED scheme either.

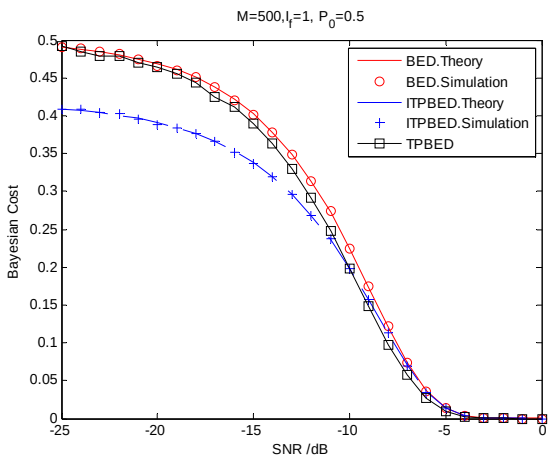

Fig. 4. Bayesian costs of three schemes against SNR

The phenomena above can be explained as follows. Without using temporal persistence, BED scheme has the worst performance. Within low SNR region, detection result of BED scheme is

unreliable, thereby ITPBED scheme that does not perform BED when the previous detection results are '10' or '01' has the better performance compared with TPBED scheme.

Conclusions

This paper considers 2 slots temporal persistence, and proposes the ITPBED scheme. We show that, compared with TPBED or BED, within low SNR regions, ITPBED scheme can greatly improve the performance. Although we only consider 2-slot temporal persistence, the proposed scheme may be better in M-slot (M > 2) temporal persistence.

Acknowledgements

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