A New Adaptive Sensing Scheme for Low SNR and Random Arrival of PU Environment

Xianzhong Xie, Ting Song, Bin Ma, and Xiaofeng Hu
Chongqing Key Lab of Mobile Communications Technology, Chongqing University of Posts and Telecommunications, Chongqing 400065, China
Email: xiexzh@cqupt.edu.cn; {songtingcqupt; huxfcqupt}@163.com; mabin@cqupt.edu.cn

***Abstract*—**Cognitive radio (CR) networks facing with difficulties caused by the low SNR environment and the random arrival of primary users (PUs) application traffic. The existing studies focus on the unilateral processing on weak PU signal or random departure/arrival of PU problems. In this paper, we propose an adaptive sensing scheme which is applicable under certain adverse conditions by jointly optimize sensing and transmission period. At first the adaptive sensing state model is established. On this basis, secondary users (SUs) perform collaborative detection in the sensing period and an optimal sensing duration is determined to obtain adaptability and detection reliability. At the end of each period, a decision-making system predicts PU's activity based on the previous observations and adaptively chooses whether to perform spectrum sensing, data transmission or channel switching. Both the impact of non-ideal sensing and the imperfect ACK/NACK feedback are being fully considered when designing the decision-making algorithm. Numerical results show that our optimal scheme significantly increases SU utility while avoiding interference to PU in the adverse environment, and it reduces detection difficulty and computational complexity.

***Index Terms*—**Cognitive radio, low SNR, random departure/arrival of PU, POMDP, adaptive spectrum sensing

I. Introduction

With the rapid development of wireless technologies, the demand for radio resources increases dramatically. Cognitive Radio (CR), as an agile radio technology, has been greatly concerned to promote the utilization of spectrum [1]. In CR networks, the secondary users (SUs) must perform periodic spectrum sensing [2] before their own data transmission so as to avoid interference with the primary users (PUs).

However, the traditional periodic sensing scheme is challenged. In practical environment, due to the imperfect channel condition such as pathloss and shadowing, the signal from the PU is so weak that the SU should prolong sensing time to guarantee detection accuracy, this comes at the expense of transmission [3]. Moreover, the SU has to constantly carry out sensing to detect the reappearance of PU when the PU randomly departs or arrives at high frequencies [4]. Long sensing duration and frequent sensing times result in a decrease in transmission period, thereby reducing the channel utilization of the secondary network.

Therefore, under low SNR environment combined with random variation of PU activities, it's of great significance to study how to maximize utilization of the SU while protecting the primary transmission out of interference. The existing works are mainly about unilateral solutions to low SNR signal [5], [6] or random departure/arrival of PU [7], [8], but these studies only settle one aspect of the problem, there is still lack of an effective solution to work out the problem fundamentally. In this paper, sensing and transmission periods are jointly considered, we propose an optimal adaptive sensing technique which is applicable under certain adverse conditions.

There are some studies jointly consider sensing and transmission stages and propose sensing-transmission schemes to improve the performance of CR network. The authors of [9-11] considered the tradeoff between sensing duration and achievable throughput, find an optimal sensing time to make the transmission time for SU as long as possible under the constraint that the PU is sufficiently protected. But these studies still adopt the "Listen-Before-Talk" strategy and belong to the type of traditional periodic sensing. While periodic sensing simplifies the design of PHY/MAC protocol, its performance significantly degrades under adverse conditions. For example, in [11], the optimized sensing time is more than 10ms in Rayleigh-fading channels, it's a rather long time in short spectrum opportunity environment which last on the order of milliseconds. Therefore, it is necessary to propose a new sensing strategy to deal with the difficulties in weak signal from the PU with fast channel-usage variation.

Manuscript received September 12, 2013; revised February 4, 2014.
This paper was supported by the National Nature Science Foundation of China under contract number 61271259 and 61301123, the Chongqing Nature Science Foundation under contract number CTSC2011jjA40006, the Research Project of Chongqing Education Commission under contract number KJ120501, KJ120502 and KJ120536, the special fund of Chongqing key laboratory (CSTC), the Program for Changjiang Scholars and Innovative Research Team in University (IRT2129), and the project of Chongqing Municipal Education Commission under contract number Kjzh11206.
Corresponding author email: xiexzh@cqupt.edu.cn.
doi:10.12720/jcm.9.3.262-270

In [12], the authors indicated that the SU couldn't have the full knowledge of the availability of all the channels, it's a partially observable result. They developed an analytical framework for opportunistic spectrum access by using the Partially Observable Markov Decision Process (POMDP). [13] investigated the problem of distributed channel selection using a game-theoretic stochastic learning solution in an opportunistic spectrum access system where the channel availability statistics and the number of the secondary users are unknown. But the research of [12], [13] focus on channel selection problem and aim to access the channel which is most likely to be vacant. While this article proposes an adaptive sensing-transmission scheme, SUs utilize the observations results about PUs and adaptively choose whether to perform spectrum sensing, transmit data or channel switching. [14], [15] also formulated the CR as a POMDP and proposed an optimal spectrum access policy. A utility function is defined to reward the SU for successful transmissions and to penalize it for colliding with the PU. The optimal action is decided by using value iteration to maximize the utility function. However, [14], [15] mainly concentrate their works on the relationship between the collision penalty factor and average utility, and the research is under single PU band and single SU. Our work bases on the cases with multiple PU bands and multiple SUs, proposes a threshold-based adaptive sensing scheme, and studies the relationship between the threshold and SUs performance. Moreover, the sensing/transmission durations of [14], [15] are a few milliseconds, the time is not short enough in fast PU state variation scenarios. While we set the sensing and transmission periods much shorter, meanwhile search for a method to make sensing reliable. SUs can adaptively schedule multiple sensing or transmission actions which decided by PUs activities.

Reference [16] designed an adaptive sensing scheme to maximize spectrum utilization in adverse environment based on POMDP. In [16], sensing and transmission periods are set to be very short (0.1ms) to enhance the adaptability of CR, the adaptive sensing CR adaptively determines next actions at consecutive decision epochs. The structure is flexible and robust to fast PU state variation. But there exists some problems:

- To increase sensing reliability in such short sensing period, [16] takes the test statistic as a soft "sensing result", and has to quantize the energy detector's sensing result to produce a quantized sensing result, the process is complicated and cause to high complexity in decision-making algorithm .
- To quantize the sensing result, the quantization levels and quantization thresholds under a certain SNR value should be accurately determined. [16] directly utilizes the empirical value of quantization levels and thresholds when the SNR is -10dB. But in practical environment, the PU SNR is often changed, [16] can't quantize the sensing result under random variation SNR environment, so the scheme is not practical.
- In CR network, there are inevitable exist false-alarm probability and missed detection probability in sensing period, the transmission process is also non-ideal. While [16] assumes sensing and transmission process are both ideal when designing the algorithm, it leads to unreliability of the adaptive sensing CR.

To tackle these problems, this paper builds on the study in [16] and makes the following contributions:

First of all, the new adaptive sensing system model is established, we fully consider the probabilities of false-alarm and missed detection in sensing period, we also account for the imperfect transmission in transmission period. Secondly, instead of using the quantized sensing method, in our scheme, SUs perform collaborative energy sensing in each sensing slot, and we attempt to determine an appropriate sensing period to obtain detection reliability and adaptability. Furthermore, when we design the decision-making algorithm, the problems caused by non-ideal sensing are being fully considered, we also research how the impact of unreliable ACK/NACK feedback information which indicates the activity of the PU during transmission period on decision-making algorithm. Simulation results show that our optimal strategy significantly increases SU utility, while avoiding interference to PU in the adverse environment, and reduces the detection difficulty and computational complexity.

The rest of this paper is organized as follows. The adaptive sensing state model is presented in Section II. Section III proposes the new adaptive sensing scheme based on POMDP. Simulation results are established in section IV. Section V offers the concluding remarks.

II. Adaptive Sensing State Model

A. PU Model

There are M authorized channels (PUs) which are independent and identically distributed (i.i.d). The PUs state alternates between busy/idle which can be modeled as a Markov process. The idle and busy periods follow the exponential distribution and we assume that SUs know distribution of PUs.

B. SU Model

We consider there are N SUs in a CR network. SUs select one channel each time to carry out collaborative sensing, and access the channel if the sensing result is free. SUs can perform sensing, transmission and channel switching (only one action in each time slot) on the free channel. They must leave and switch to the next channel when the PU returns. Choose one of SUs as the decision-making system, it makes decision on the next

action at the end of each time slot, it also allocates time for each SU when SUs conduct data transmission.

C. Adaptive Sensing State Model

In the adaptive sensing strategy, each sensing and transmission period is short, SUs can continuous schedule multiple sensing or transmission actions, therefore adaptively adjust the sensing and transmission durations on the basis of PUs activities. The state model is shown in Fig. 1.

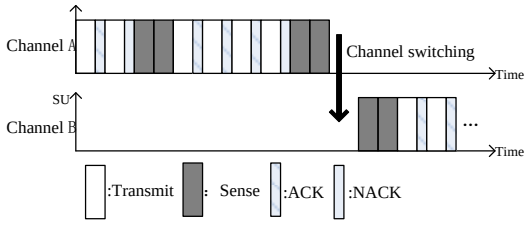

Fig. 1. Adaptive se nsing state model.

The following are the detailed descriptions of SUs actions.

1) Spectrum sensing time slot

At the end of time slot t, if the decision-making algorithm is not sure whether the PU exists or not, it chooses spectrum sensing at time slot t+1. Each SU employs energy detector for sensing which the time duration is T_S, the bandwidth of the interest channel is W and γ is the received SNR.

SUs adopt cooperative sensing to improve detection reliability. Each SU senses the PU individually and sends their local sensing result to the specified SU, the specified SU combines local sensing results using the K/N rule[17]. We assume that the sensing result is idle only if the channel is idle during the whole sensing period.

Due to the imperfect sensing, the false-alarm probability and detection probability are introduced. The probability of false alarm at each SU is $P_{f,\ i}$, assumes all SUs employs the Neyman-Pearson criterion to generate a binary hard decision, the detection probability as follows[17] :

$$P_{d,i} = Q\left[\left(1/\sqrt{2\gamma+1}\right)/\left(Q^{-1}(P_{f,\ i}\right) - \sqrt{WT_S}\,\gamma\right] \tag{1}$$

After N SUs cooperative sensing, the detection probability is:

$$P_D = \sum_{k=K}^{N}\binom{N}{k}\left(P_{d,i}\right)^k\left(1-P_{d,i}\right)^{N-k} \tag{2}$$

The false-alarm probability for the system is:

$$P_F = \sum_{k=K}^{N}\binom{N}{k}\left(P_{f,i}\right)^k\left(1-P_{f,i}\right)^{N-k} \tag{3}$$

2) Data transmission time slot

When the decision-making algorithm shows that the channel has a high probability to be free at t, then SUs transmit data at t+1. The SUs use the time-division multiple-access scheme during the transmission period.

Although the SU cannot detect the PU signal during transmission period, the SU receiver sends ACK/NACK feedback to the SU transmitter to notify weather the transmission is successful. In ideal case, when the SU transmitter receives ACK, it considers the PU is inactive and the packet is successfully transmitted; while the reception of NACK means the channel is occupied by PU. By this kind of acknowledgement, the CR can get hold of PU activity.

However, in wireless communication, the SU receiver has a certain ability to capture, it may decode the packet when collision happens. Otherwise, under the non ideal channel condition, a NACK can be received even if the channel is free. We define $X1$ is the probability that the SU transmitter receives NACK although no collision happens, $X2$ is the probability that a NACK is received when SU collide with PU. Usually $0<X1<X2<1$, this paper will fully analyze the impact of non ideal ACK/NACK on the adaptive sensing scheme.

3) Channel switching time slot

When the decision-making algorithm indicates that PU returns to the channel at t, then SUs immediately abandon this channel and access next new channel at t+1.

III. Adaptive Sensing Scheme Based On POMDP

We can learn that decision-making algorithm is the key of the adaptive sensing scheme from section III. The decision-making system chooses the next action for SUs based on the observations at current time slot. Through the way of adaptive decision-making process, SU can avoid unnecessary sensing and improve spectrum efficiency.

In CR networks，because of hardware and energy constraints, SU could only get a partially observable results both in the sensing and transmission period. The process of make decisions based on partially observation information is a POMDP. Here we give the POMDP model.

A. POMDP Model

The POMDP model is defined by the following sets.

1) PU state

Using s_t define PU state at t, s_t={0(idle),1(busy)}.

2) SU action

Let a_t express SU action at t, the SU can perform sensing, transmission or channel switching, a_t ={S, T, C}.

3) PU state transition probability

Assume that PU idle/busy periods are independent which follow exponential distribution. The PU transfers from idle to busy with rate λ, and transfers from busy to idle with rate μ. Then the authorized channel stays in idle/busy period with average time of $1/\lambda$ and $1/\mu$ respectively.

The cumulative distribution function (CDF) of the PU idle/busy time is:

$$\begin{cases} F_{idle}(t) = 1 - e^{-\lambda t} \\ F_{busy}(t) = 1 - e^{-\mu t} \end{cases} \tag{4}$$

The probability that the PU will remain idle during the sensing period (T_S) or transmission period (T_D) is:

$$\begin{cases} g_t^S = \dfrac{1 - F_{idle}(t + T_S)}{1 - F_{idle}(t)} = e^{-\lambda T_S} \\ g_t^T = \dfrac{1 - F_{idle}(t + T_D)}{1 - F_{idle}(t)} = e^{-\lambda T_D} \end{cases} \tag{5}$$

The stationary probability for PU remains idle is:

$$g_{idle} = \mu / (\lambda + \mu) \tag{6}$$

4) Observation results

Observations can be obtained when a corresponding action finished. If the SU conduct spectrum sensing, the observation result is idle or busy; if the SU action is transmission, then it gets ACK /NACK feedback information; when the SU perform channel switching, there is no observation result.

5) Objective function

In the POMDP model, the objective function is total expected reward the SU can get for taking action a_t in state s_t, the objective function is given by:

$$E\left[\sum_{t=1}^{\infty} \beta^t R(s_t, a_t)\right] \tag{7}$$

β is a discount factor which make the objective function bounded. $0<\beta<1$, it's very close to 1.The goal of the decision-making system is choosing the best action for SUs at each time slot to maximize the objective function.

B. The Updating Algorithm of Belief Vector

After getting the POMDP model, the decision-making algorithm will calculate a belief vector based on the POMDP. The belief vector reflects the state of PU and contains all the necessary information for making an optimal decision, we can find an optimal action according to it.

In this paper the belief vector refers to the SU's estimation on the PU idle probability $P(t)$. The following will explain how to calculate it under the action of sensing, transmission and channel switching when give full consideration to the impact of non-ideal sensing and the imperfect ACK/NACK feedback. When the SU first accesses a channel, the initial idle probability is given as the stationary probability, namely $P(t)=\mu/(\lambda+\mu)$.

1) Spectrum sensing

Under the action of spectrum sensing, each SU senses the PU individually and gets a local sensing result, then sends them to the specified SU, the specified SU combines these results and makes a final decision. The probability that the sensing outcome is free is:

$$W_S^I = g_t^S P(t)(1 - P_F) + \left[1 - g_t^S P(t)\right](1 - P_D) \tag{8}$$

The belief vector can be achieved by using Bayes rule:

$$P_S^I(t+1) = g_t^S P(t)(1 - P_F) / W_S^I \tag{9}$$

The probability of a busy sensing result is:

$$W_S^B = g_t^S P(t) P_F + \left[1 - g_t^S P(t)\right] P_D \tag{10}$$

Then we get the belief vector in the same way:

$$P_S^B(t+1) = g_t^S P(t) P_F / W_S^B \tag{11}$$

2) Date transmission

In transmission period, the SU transmitter takes the ACK/NACK acknowledgement as observation to estimate whether the PU is active. Due to the imperfect ACK/NACK feedback ($0<X1<X2<1$), the probability that the SU receives an ACK is:

$$W_T^A = g_t^T P(t)(1 - X_1) + \left[1 - g_t^T P(t)\right](1 - X_2) \tag{12}$$

The probability that the PU is idle after the SU receives an ACK is:

$$P_T^A(t+1) = g_t^T P(t)(1 - X_1) / W_T^A \tag{13}$$

Similarly, the probability that the SU receives a NACK is:

$$W_T^N = g_t^T P(t) X_1 + \left[1 - g_t^T P(t)\right] X_2 \tag{14}$$

In this case the belief victor is updated as follows:

$$P_T^N(t+1) = g_t^T P(t) X_1 / W_T^N \tag{15}$$

When $X_1=0$，$X_2=1$, it is ideal case, the idle probability of the PU is updated for:

$$P_T(t+1) = g_t^T P(t) \tag{16}$$

3) Channel switching

If the SU performs channel switching at t, then it will access a new channel later on, the PU idle probability is the stationary probability, i.e. $P_C(t+1)=\mu/(\lambda+\mu)$.

C. Optimal Policy Based on POMDP

After getting the updating algorithm of $P(t)$ under non-ideal sensing and imperfect ACK/NACK feedback situation, the decision-making system chooses the next action for SUs based on the value of $P(t)$. The optimal action is the one that maximizes the objective function (7). In this section we achieve to find the optimal policy.

In order to find the optimal policy, we transform the problem of POMDP optimal policy to "belief MDP "optimal policy[18], and formulate new reward functions $S(P(t),t)$, $T(P(t),t)$, $C(P(t),t)$, then came to the optimal value function according to Bellman equation[19]:

$$V(P(t),t) = \max\left\{S(P(t),t), T(P(t),t), C(P(t),t)\right\} \tag{17}$$

where $V(P(t),t)$ is the maximum expected reward the SU can obtain at time t when the optimal policy adopted.

$S(P(t),t)$, $T(P(t),t)$, $C(P(t),t)$ are the expected rewards for taking the action of spectrum sensing, data transmission and channel switching respectively.

Next we discuss how to formulate $S(P(t),t)$, $T(P(t),t)$, $C(P(t),t)$. Considering uncertainty of the POMDP model and the long-term reward function, we need to construct a reward function between belief vector and reward value. It not only includes the immediate reward under current action, but also considers long term effect for taking certain action.

1) Reward function for spectrum sensing

If the action of the SU is sensing, the immediate reward can be obtained as follows:

$$R_S^M = P(t)R(0, S) + [1 - P(t)]R(1, S) \tag{18}$$

where $R(0, S)/R(1, S)$ is the immediate reward when the sensing result is free/busy. Since time and energy are consumed for sensing, the value of $R(0, S)$ and $R(1, S)$ should be zero or negative.

The future reward is given by:

$$R_S^L = W_S^I V\left(P_S^I(t+1), t+1\right) + W_S^B V\left(P_S^B(t+1), t+1\right) \tag{19}$$

Then the reward function for spectrum sensing is:

$$S\left(P(t), t\right) = R_S^M + \beta R_S^L \tag{20}$$

2) Reward function for data transmission

The immediate reward that the SU obtains after data transmission is:

$$R_T^M = P(t)R(0, T) + [1 - P(t)]R(1, T) \tag{21}$$

where $R(0, T)$ is a positive value, because data are successfully transmitted when transmission action is selected in state 0. If transmission is selected in state 1, a collision occurs, therefore $R(1, T)$ should be a negative value. The larger $R(1, T)$, the greater punishment to SU when a collision happens ,the better protection of PU.

The future reward is:

$$R_T^L = W_T^A V\left(P_T^A(t+1), t+1\right) + W_T^N V\left(P_T^N(t+1), t+1\right) \tag{22}$$

The reward function for data transmission is:

$$T\left(P(t), t\right) = R_T^M + \beta R_T^L \tag{23}$$

3) Reward function for channel switching

The immediate reward is

$$R_C^M = P(t)R(0, C) + [1 - P(t)]R(1, C) \tag{24}$$

Since the channel switching process spends a long time and consumes energy, $R(0, C)$and $R(1, C)$ should be negative.

The future reward is:

$$R_C^L = V\left(P_C(t+1), t+1\right) \tag{25}$$

Finally, we get:

$$C\left(P(t), t\right) = R_C^M + \beta R_C^L \tag{26}$$

After get the reward function, the optimal policy is as follows:

Calculate the three rewards at the end of time slot t: if $S(P(t),t)>\max\{T(P(t),t), C(P(t),t)\}$,next action is sensing; if $T(P(t),t)>\max\{S(P(t),t), C(P(t),t)\}$,then transmit data; if $C(P(t),t)>\max\{T(P(t),t), S(P(t),t)\}$, perform channel switching for next action.

Thereby we find the optimal policy that achieves the maximum reward function.

D. Threshold Structure and Algorithmic Process

The optimal value function can be calculated by using value iteration or backward induction, but this method has a larger time overhead and high computational complexity. This paper takes the analysis results of [16] for reference and exploits a threshold structure to simplify the calculation.

Firstly set two thresholds H and L, then at the end of each time slot, compare the updated belief vector $P(t)$ with two thresholds, if $P(t)>H$, it indicates that the PU has a high probability to be free and SU could transmit data next action; if $L<P(t)<H$, it uncertain about the PU activity and more sensing is needed to detect the PU; $P(t)<L$ shows that the PU is very likely to exist, then SUs have to switch to another channel. This kind of threshold-based structure significantly reduces time overhead and decreases computational complexity compared to value iteration method, thus the decision-making system can make decisions quickly. Fig. 2 gives the process of adaptive sensing algorithm. We will analysis the relationship between the threshold and SUs performance in Section IV.

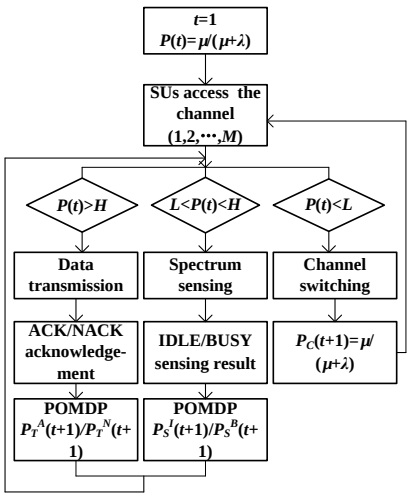

Fig. 2. Process of adaptive sensing algorithm.

IV. Simulation Results

Considering all simulations are conducted using a BPSK modulation on the AWGN channel. There are M authorized channels, the bandwidth of which is 1MHz. The channel stays in idle/busy period for $1/\lambda=1/\mu=10$ms

(random departure/arrival of PU). Unless otherwise noted, the SNR of the PU signal is −10 dB (low SNR environment). Assume there are 3 SUs which are in a small-scale network. All SUs employ the energy detector to generate a binary hard decision, choose one of the SUs as the fusion center, it makes the final decision by majority rule. Consider the impact of non-ideal sensing, we set P_F=0.1; and the imperfect transmission, set X_1=0.2, X_2=0.8. In addition, we let sensing time is the same as transmission time, i.e. T_S=T_D, the channel switching time T_C=1ms.

For simulations, the "channel utilization" refers to the SU successful transmission time without interrupting the PU. Successful transmission means the SU transmits data and gets an ACK feedback when the channel is idle. The "collision probability" is the proportion of time which the SU transmit data when the channel is occupied by the PU. We define the "channel-switching time proportion" is the proportion of time that the SU spend on channel switching process.

Firstly we simulate to find an appropriate sensing period. Set L=0.4, H=0.8/0.85, Fig. 3 shows the variation of channel utilization and collision probability when the sensing time changes. We can see from Fig. 3 that as T_S changes from 0.1m-0.2ms, the channel utilization decreases slightly, while the collision probability significantly decreases. The lower H, the greater decreases of collision probability, when T_S=0.2ms, the collision probability is in a low range. Meanwhile, consider the sensing time of the adaptive sensing scheme should be as short as possible to meet adaptability, we determine T_S=0.2ms is an appropriate sensing period.

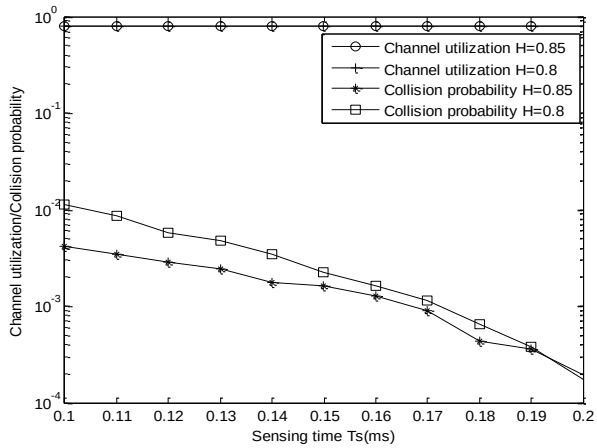

Fig. 3. Channel utilization / collision probability according to sensing time.

Secondly, we consider the random variation SNR in low SNR (SNR-10dB or less) environments. In practical, the PU SNR is always changes randomly, the adaptive sensing strategy in [16] cannot be used in the SNR randomly changing environment, this paper effectively solves this problem. Fig. 4 shows when the SNR of the PU randomly changes from -10dB-12dB, the updated $P(t)$ over time.

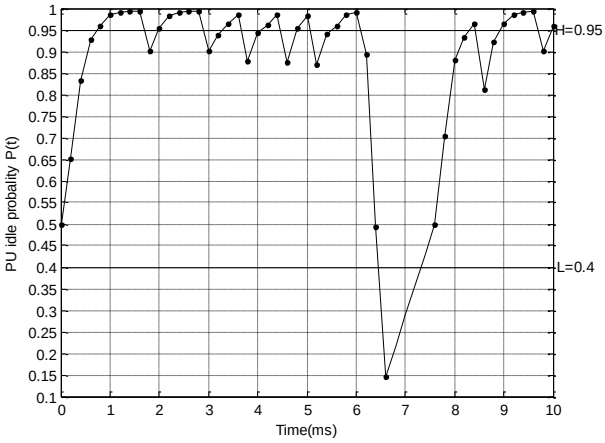

Fig. 4. The variation of PU idle probability over time.

Assuming that the channel is free at 0-5.8ms, and the PU returns at 6ms. The points in Fig. 4 represent the values of $P(t)$. As can be seen from Fig. 4, when the SNR of the PU changes randomly, SUs still has a good detection performance. When the channel is idle, SUs can perform adaptive sensing or transmission according to the updated $P(t)$ values every time (the points between 0.4-0.95 represent that SUs are conducting spectrum sensing, when $P(t)$ exceed 0.95, SUs perform data transmission). When the PU appears, SUs can accurately detect the PU immediately, and promptly switch to next channel to avoid collisions (the points which are below 0.4 means that the values of $P(t)$ are less than 0.4, at this time SUs perform channel switching).

By this mechanism, SUs adaptively schedule multiple sensing/transmission operations and find out the appropriate sensing/transmission durations on the basis of $P(t)$, therefore avoiding unnecessary sensing meanwhile exploiting the temporary spectrum opportunities. This is why our adaptive sensing scheme outperforms the traditional periodic sensing method.

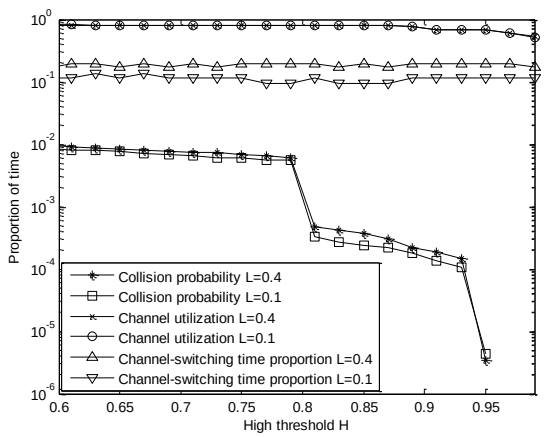

Fig. 5. Channel utilization/collision probability/ channel-switching time proportion according to H and L (imperfect ACK/NACK).

Fig. 5 consider the impact of non ideal sensing (P_F=0.1) and non ideal transmission (X_1=0.2, X_2=0.8), simulate the relationship between the channel utilization/collision probability/channel-switching time proportion and thresholds respectively.

It can be found from Fig. 5, the threshold H determines channel utilization and collision probability, the threshold L determines the channel-switching time proportion. With H value increases, channel utilization and collision probability decrease. Because as H increases, the SU could transmit data when the $P(t)$ achieves a higher value, thereby resulting in a decrease in channel utilization. However, the benefit is that the collision probability also decreases, and better protection can be provided for the PU. We can see from Fig. 5, when H is about 0.8, the collision probability drops by nearly two orders of magnitude. Therefore, we can determine the value of H according to channel utilization and collision probability curves in Fig. 5 to meet the system channel utilization and collision probability requirements. Further, the higher the L, the more frequently the SU switches channel; the lower the L, the SU stays on the channel more stable, so we can select L to determine the frequency of channel switching.

Fig. 6 considers the case without ACK/NACK acknowledgement, the transmission is successful only when there is not collision occurs.

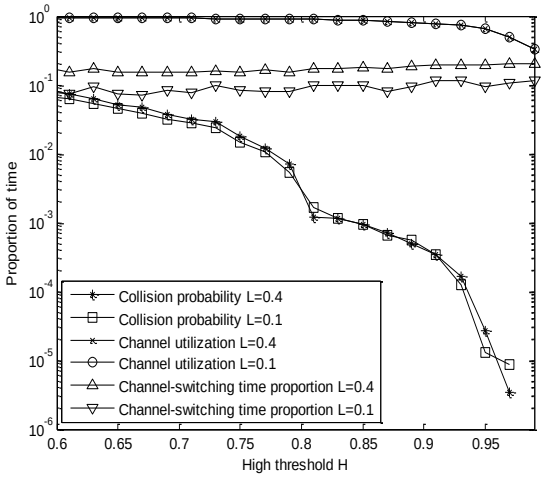

Fig. 6. Channel utilization/collision probability/channel-switching time proportion according to H and L (without ACK/NACK).

We can get the same conclusions from Fig. 6: H decides channel utilization and collision probability, L determines channel-switching time proportion. In Fig. 6, the channel utilization is higher than that in Fig. 5, this is inevitable. Because Fig. 6 considers ideal transmission conditions, as long as the SU performs transmission in the free channel, this transmission must be successful; while Fig. 5 considers the non ideal channel effects, the successful transmission probability on free channel condition is 1-X_1=0.8. Moreover, we find that under the same H values, the probability of collision in Fig. 6 is higher than Fig. 5. This indicates that sending ACK/NACK in transmission process can make the SU learn the activity of the PU, then the updated $P(t)$ is more accurate, thus effectively reducing the collision probability.

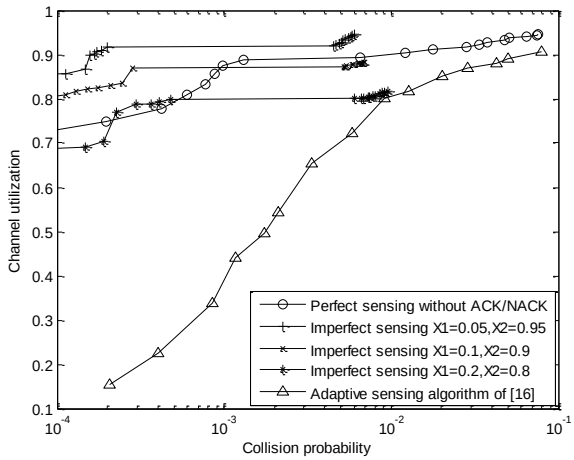

Fig. 7. Compare the performance between the new adaptive scheme and [16].

In Fig. 7, we compare our new adaptive sensing scheme with [16] in terms of channel utilization and collision probability. We obtain the curves by changing the thresholds H and L.

In this simulation, we consider the following four cases: ideal transmission, without ACK/NACK; non ideal transmission: $X1$=0.05, $X2$=0.95, $X1$=0.1, $X2$=0.9, $X1$=0.2, $X2$=0.8. As can be seen, when considering the non ideal transmission, smaller $X1$ and greater $X2$ result in higher channel utilization. This is because, $X1$ and $X2$ values indicate estimation accuracy for whether the PU exists. The smaller of $X1$ and greater $X2$ mean the more accurate estimation of the PU activity, and the updated $P(t)$ is more accurate, thereby improving channel utilization and reducing collision probability.

Comparing this paper's non ideal transmission case with [16], it can be found that when the collision probability is 10^{-4}-10^{-2}, the channel utilization in our scheme is significantly greater than [16]; when the collision probability is higher than 10^{-2}, the channel utilization continues to increase in [16], but in this paper it has already reached its maximum. This is because, at 10^{-4}-10^{-2} collision probability, the corresponding threshold H of our technique is 0.99-0.6, such low H provides more transmission opportunities for the SU, thereby resulting in high channel utilization. Meanwhile, our optimal algorithm improves the detection reliability and estimation accuracy of the PU, although under such low H values, the collision can still be controlled in a low range. However, in [16], the corresponding threshold is 0.999-0.98 when the collision probability at 10^{-4}-10^{-2}, such a high threshold causes few transmission opportunities so the channel utilization is so poor. With collision probability increases, H in [16] could continue

to decrease, and the channel utilization improves continuously; while in our method, the value of H has been taken to 0.6, cannot decrease any more.

V. Conclusions

Aiming at the problems existing in spectrum sensing, this paper proposes an optimal adaptive sensing technique, firstly the SUs perform cooperative sensing and an appropriate sensing period is determined to obtain adaptability and detection reliability; then the CR predicts PU's activity based on the previous observations and adaptively chooses the next action for SU. Compared with the previous adaptive sensing strategy, our optimal method reduces computational complexity and could be applied to the random variation SNR environment, meanwhile considers the impact of non-ideal sensing and the imperfect transmission. Results show that, in low SNR combined with fast PU state variation scenarios, the optimal scheme significantly increases SU utility than the traditional scheme.

References

[1] J. Mitola and G. Q. Maguire, "Cognitive radios: making software radios more personal," *IEEE Personal Communications*, vol. 6, no. 4, pp. 13-18, 1999.

[2] L. Lu, X. W. Zhou, U. Onunkwo, and G. Y. Li, "Ten years of research in spectrum sensing and sharing in cognitive radio," *EURASIP Journal on Wireless Communications and Networking*, 2012.

[3] Y. Zou, Y. D. Yao, and B. Zheng, "Outage probability analysis of cognitive transmissions: Impact of spectrum sensing overhead," *IEEE Transactions on Wireless Communications*, vol. 9, no. 8, pp. 2676-2688, 2010.

[4] S. C. A. Chu, A. S. Alfa, and J. Cai, "A model for bursty PU channel and its impact on the study of cognitive radio networks," in *Wireless Communications and Mobile Computing Conference (IWCMC)*, Sardinia, 2013, pp. 461 - 466.

[5] M. Loper-benite and F. Casadewall, "Improved energy detection spectrum sensing for cognitive radio," *IET Communications*, vol. 6, no. 8, pp. 785-796, 2012.

[6] A. S. B. Kozal, M. Merabti, and F. Bouhafs, "An improved energy detection scheme for cognitive radio networks in Low SNR Region," in *Proc. IEEE Symposium on Computers and Communications*, Cappadocia, 2012, pp. 684-689.

[7] L. Tang, Y. F. Chen, E. L. Hines, and M. S. Alouini, "Performance analysis of spectrum sensing with multiple status changes in primary user traffic," *IEEE Communications Letters*, vol. 16, no. 6, pp. 874-877, 2012.

[8] J. Shim, Y. Lee, Y. Lee, and S. Yoon, "A novel spectrum sensing scheme for dynamic pu traffic environments," *Wireless Conference (EW)* , Guildford, UK, 2013, pp.1 - 4 .

[9] X. Z. Xie and Z. C. Lv, "Analysis of optimal sensing duration with power control and partial primary user's information," in *Proc. IEEE ISCIT*, Hangzhou, China, 2011, pp. 103-108.

[10] Y. J. Choi, W. Pak, Y. Xin, and S. Rangarajan, "Throughput analysis of cooperative spectrum sensing in Rayleigh-faded cognitive radio systems," *IET Communications*, vol. 6, no. 9, pp. 1104-1110, 2012.

[11] D. Sun, T. C. Song, M. Wu, J. Hu, J. Guo and B. Gu, "Optimal sensing time of soft decision cooperative spectrum sensing in cognitive radio networks," in *Proc. Wireless Communications and Networking Conference*, Shanghai, China, 2013, pp. 4124-4128.

[12] Q. Zhao, L. Tong, A. Swami, and Y. X. Chen, "Decentralized cognitive MAC for opportunistic spectrum access in ad hoc networks: a POMDP framework," *IEEE Journal on Selected Areas in Communications*, vol. 25, no. 3, pp. 589-600, 2007.

[13] Y. H. Xu, J. L. Wang, and Q. H. Wu, "Opportunistic spectrum access in unknown dynamic environment: A game-theoretic stochastic learning solution," *IEEE Transactions on Wireless Communications*, vol. 11, no. 4, pp. 1380-1392, 2012.

[14] S. Huang, X. Liu, and Z. Ding, "Optimal sensing-transmission structure for dynamic spectrum access," in *Proc. IEEE INFOCOM 2009*, Rio de Janeiro, Brazil, 2009, pp. 2295-2303.

[15] W. Afifi, A. Sultan, and M. Nafie, "Adaptive sensing and transmission durations for cognitive radio," in *Proc. IEEE DySPAN*, Aachen, Germany, 2011, pp. 380-388.

[16] K. W. Choi, "Adaptive sensing technique to maximize spectrum utilization in cognitive radio," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 2, pp. 992-998, 2010.

[17] R. Viswanathan and V. Aalo, "On counting rules in distributed detection," *IEEE Transactions on Speech and Signal Processing*, vol. 37, no. 5, pp. 772-775, 1989.

[18] L. P. Kaelbling, M. L. Littmen, and A. R. Cassandra, "Planning and acting in partially observable stochastic domains," *Artificial Intelligence*, vol. 10, no. 1, pp. 99-134, 1998.

[19] G. E. Monahan, "A survey of partially observable Markov decision processes: Theory, models, and algorithms," *Manage. Sci.*, vol. 28, no. 1, pp. 1–16, 1982.

Xianzhong Xie received his Ph.D. degree in communication and information systems from Xi'dian University, China, in 2000. He is currently with the School of Computer Science and Technology at Chongqing University of Posts and Telecommunications, China, as a professor and director of the Institute of Broadband Access Technologies. His research interests include cognitive radio networks, MIMO precoding, and signal processing for wireless communications. He is the principal author of five books on cooperative communications, 3G, MIMO, cognitive radio, and TDD technology. He has published more than 120 papers in journals and 45 papers in international conferences. Email: xiexzh@cqupt.edu.cn.

Ting Song received her B.S. degree from the PLA information engineering university, China, in 2011. She is a postgraduate student of Chongqing University of Posts and Telecommunications, China, and will receive her M.S. degree in communication and information systems in 2014. Her research interests include cognitive radio networks, cooperative communications and wireless communications. Email: songtingcqupt@163.com

Bin Ma received the M.S. Degree in computer software and theory in 2007. He is currently an associate professor at Chongqing University of Posts and Telecommunications, Chongqing, China. He has published over 20 academic journal and conference papers in cognitive radio networks, heterogeneous wireless network and trust management. His

recent work focuses on spectrum handover in cognitive radio networks and vertical handoff in heterogeneous wireless networks. Email: mabin@cqupt.edu.cn.

Xiaofeng Hu was born in Nantong of Jiangsu Province in 1987. He received his B.S. degree from Nanjing Institute of Technology, China, in 2011. He is a postgraduate student of Chongqing University of Posts and Telecommunications currently, China, and will receive his M.S. degree in communication and information systems in 2014. His research interests include cognitive radio networks, cooperative communications and wireless communications.