Enhanced Throughput of Cognitive Radio Networks by Imperfect Spectrum Prediction

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Abstract—Spectrum sensing is used to detect spectrum holes and find active primary users while randomly selecting channel for sensing lead to secondary user’s low throughput in high traffic cognitive radio networks. Spectrum prediction forecasts future channel states on the basis of historical information. A new frame structure is proposed in this letter for the imperfect spectrum prediction, resulting to select channels for sensing only from the channels predicted to be idle. Simulation results show that secondary user’s throughput is significantly enhanced by imperfect spectrum prediction. The impacts of traffic intensity, prediction errors, and channel number on the throughput are also investigated in this study.

Index Terms—Imperfect spectrum prediction, cognitive radio networks, frame structure.

I. INTRODUCTION

COGNITIVE radio has attracted an increasing amount of interest over the past decade as an effective solution to alleviate spectrum scarcity in wireless communications, which allows the secondary users (SUs) access frequency bands pre-allocated to primary users (PUs) in a way that primary users do not be interfered [1]. As an essential step, spectrum sensing ensures that SUs sense PUs and detect spectrum holes timely: SUs access the channels and transmit data when PUs are absent in the licensed channels; otherwise, SUs wait or select another channel for sensing [2]. In high traffic Cognitive Radio Networks (CRN), the probability of PU channels been occupied is high. If SUs randomly select channels for sensing, it will lead to the high probability of sensing busy and further results in the decrease of throughput. SU’s low throughput has a negative effect on the CRN’s performance, such as prolonging the transmission time and increasing the energy consumption. Therefore, this issue has been extensively investigated. In [3], amplify-and-forward relays were used for joint optimization of the spectrum sensing and data transmission, which significantly improves SU’s throughput in comparison with traditional mechanisms. In [4], SUs’ frame structure was designed to sense channels in order, and the historical data is combined to select the channels for sensing, so as to achieve the largest throughput.

In existing work, few works attempt to improve SU’s throughput from the perspective of reducing the probability of selecting busy channels. Traditional SU randomly selecting channels for sensing, which leads to the high probability of sensing busy in high traffic CRN and further results in a high probability of waiting. Therefore, how to increase the probability of selecting idle channels for sensing becomes the key point to improve SU’s throughput. Spectrum prediction forecasts the channel status of the next frame on the basis of historical information. Tumuluru et al. [5] employed the artificial neural network (ANN) for spectrum prediction, which can quickly predicts the channel states after the training process completed.

To solve the problem of SU’s low throughput in high traffic CRN, we redesign the SU’s frame structure in this letter by adding the spectrum prediction function. The close-form expression of SU’s throughput is derived, jointly taking into account the imperfect spectrum prediction and sufficient protection to PUs. Then we evaluate the effect of prediction errors, traffic intensity and channel number on SU’s throughput through numerical results, which prove that our design significantly improve SU’s throughput in high traffic CRN.

This letter is organized as follows. The system model is introduced in Section II. SU’s throughput under imperfect spectrum prediction is investigated in Section III. Section IV shows the numerical results, and Section V conclusions the letter.

II. SYSTEM MODEL

A CRN which can access a set of $N$ licensed frequency channels is considered. The CRN consists of a pair of SU transceivers, which access the licensed channels opportunistically. Since PU channels may be discontinuous and belong to different networks, the PUs activity on each channel can be assumed to be independent of each other. The PUs’ traffic is modeled as a binary stochastic process, i.e. busy or idle. Besides, PUs arrival time is modeled as a Poisson distribution of parameter $\lambda$ and holding time is modeled as a binomial distribution of parameter $\mu$ [6]. Therefore, the channel is busy with the probability $P(H_1) = \mu/\lambda$ and idle with the probability $P(H_0) = (\lambda - \mu)/\lambda$. Accordingly, the CRN’s traffic intensity $\rho$ is equivalent to the probability of busy $P(H_1)$, i.e., $\rho = P(H_1) = \mu/\lambda$.

In the rest of this letter, we denote SU that frame structure is redesigned as SU-P. SU-P’s frame structure is designed to consist three duration, i.e. spectrum prediction duration, spectrum sensing duration and data transmission duration, which is shown in Fig. 1. During the spectrum prediction duration, SU predicts the status of $N$ channels on the basis of the historical information. Then, SU randomly selects a channel from the channels predicted to be idle to perform spectrum sensing.

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the channel is sensed busy, SU keep waiting in the transmission duration; Otherwise, SU performs channel estimation and accesses the channel for transmissions.

Energy detection is the most popular spectrum sensing scheme, which is faster than most spectrum sensing schemes. Therefore, we apply energy detector for spectrum sensing in this study. Besides, there are many spectrum prediction schemes. In this letter, we choose neural network model for spectrum prediction [5], which using the multilayer perceptron network to construct the prediction model, which can predict repeatedly once the training process completed.

The throughput is defined as the ratio of the total transmitted data to the total time consumed. In each frame, there are three possible throughput. If the channel is sensed busy, SU-P should wait in the transmission duration and the throughput is 0. If the channel is sensed idle, SU-P access the channel and send data. While the true state of the channel is busy or idle, $C_0$ denotes the throughput of the SU-P when SU-P operates in the absence of PUs, and $C_1$ denotes the throughput when SU-P operates in the presence of PUs. Obviously, SU-P will be interfered by the present PUs during the transmission and we can derive $C_0 > C_1$. Denote $\text{SNR}_r$ as the signal noise ratio (SNR) of SU’s signal measured at SU transceiver, and $\text{SNR}_p$ as the interference SNR of PU’s signal measured at SU transceiver. It is assumed that the PUs’ activities and the SU’s activity are independent of each other. Then we have

$$ C_0 = \frac{T - \tau_s - \tau_p}{T} \log_2 (1 + \text{SNR}_r), \quad (1) $$

$$ C_1 = \frac{T - \tau_s - \tau_p}{T} \log_2 \left( 1 + \frac{\text{SNR}_r}{1 + \text{SNR}_p} \right), \quad (2) $$

where $\tau_s$ is the sensing duration, $\tau_p$ is the prediction duration and $T$ is the frame duration.

### III. Throughput Enhancement of Imperfect Spectrum Prediction

Firstly, SU-P performs spectrum prediction for $N$ channels. Spectrum prediction is a binary hypotheses test: channels are predicted to be idle or busy in the next frame. Here, the imperfect spectrum prediction is taken into account, i.e., the probability of wrong prediction is $P'_p$. Considering the channel’s true state is idle or busy, the probability distribution of true channel state and prediction is shown in Table I.

For a channel, the probability of predicting to be idle is

$$ P'_p = P(H_0) \left( 1 - P'_p \right) + P(H_1) P'_p, \quad (3) $$

While the probability of predicting to be busy is

$$ P''_p = P(H_0) P'_p + P(H_1) \left( 1 - P'_p \right), \quad (4) $$

After spectrum prediction, SU-P performs spectrum sensing only on the channels predicted to be idle. The case of “there are exactly $k$ channels predicted to be idle in the N-channel CRN” can be seen as a $k$ repeated Bernoulli trials ($k \leq N$), and the corresponding probability is $\binom{N}{k} (p^0_p)^k (p^1_p)^{N-k}$. For the whole CRN, the probability of predicting to be idle is

$$ P^0_N = \sum_{k=1}^{N} \binom{N}{k} C_N^k \left( p^0_p \right)^k \left( p^1_p \right)^{N-k}, \quad (5) $$

and the probability of predicting to be busy is

$$ P^1_N = C_N^0 \left( p^0_p \right)^0 \left( p^1_p \right)^{N-0} = \left( p^1_p \right)^N. \quad (6) $$

The probability $P^0_N$ denote that every channel in CRN is predicted to be busy in the CRN. Therefore, SU-P randomly select channel for sensing at this moment. Besides, prediction results have no effect on the sensing results and vice versa. The probability distribution of true channel state and sensing is shown in Table II.

For prediction, sensing and true channel state are independent of each other, the probability distribution is shown in Table III.
When a channel is sensed busy, SU-P has to keep waiting in the transmission duration, thus the probability of waiting is given by

\[ P_{\text{wait}} = P_2 + P_4 + P_6 + P_8. \]  

(7)

Considering the true channel states, SU-P’s average throughput is given by

\[ R_{\text{avg}} = (P_1 + P_3)C_0 + (P_5 + P_7)C_1. \]  

(8)

Eq. (8) is the closed-form expression of SU-P’s throughput under the imperfect prediction condition. According to Liang’s research in [2], SU-P’s sensing duration must be greater than the minimum to ensure that PUs are sufficiently protected. The minimum sensing duration is determined by the target detection probability \( P_d \) and the target false-alarm probability \( P_f \), which is given by

\[ \tau_{\text{min}} = \frac{1}{\gamma^2 f_s} \left( Q^{-1}(P_f) - Q^{-1}(P_d) \sqrt{2\gamma + 1} \right), \]  

(9)

where \( \gamma \) is the SNR of the SU’s signal at the SU’s transceiver, and \( f_s \) is the sampling frequency of SU’s transceiver. Generally speaking, the target detection probability \( P_d \) and the target false-alarm probability \( P_f \) are given before designing SU’s transceiver. Thus, \( P_d, P_f \) and \( \tau_{\text{p}} \) can be seen as constants. From (8), as \( P_d, P_f, \tau_{\text{p}} \) are given, SU-P’s throughput is only affected by three parameters, i.e. the probability of wrong prediction \( P_{p}^w\), the traffic intensity \( \rho \) and the channel number \( N \).

### IV. Numerical Results and Discussion

SU-P and traditional SU’s throughput are compared and discussed in this section. Unless otherwise stated, the values of the parameters used are listed in Table IV.

The standard of IEEE802.22 is the first worldwide wireless standard based on cognitive radio [8], which is used to construct the wireless regional area network (WRAN) through reusing the TV spectrum without causing harmful interference to the incumbents (i.e., the TV receivers). Therefore, the parameter setting in this letter is following the advices of IEEE802.22 WRAN Standard.

Next, the setting of prediction duration is discussed. In [6], prediction duration is evaluated as 2%–15% of the frame duration. Thus the prediction duration is 2–15 ms if the frame duration is set to 100 ms. In [7], engineers constructed a single-channel CRN experimental platform based on the universal software radio peripheral (USRP). The prediction duration, energy consumption and prediction accuracy are quantified, and the prediction duration is about 1 to 30 ms. Therefore, it is reasonable to set the prediction duration \( \tau_{\text{p}} = 5 \text{ ms} \) in this study.

The traditional SU is used for comparison in this section, which frame structure is shown in Fig. 2. Traditional SU randomly selects a channel for sensing, then accesses the channel and transmits data if the channel is sensed to be idle, or waits otherwise.

As SU’s throughput will changes as when channel number changes, SU’s throughput need to be normalized. If the SU only performs data transmission during the whole frame regardless of PU’s activities, this SU will achieve the maximum throughput, which defined as the upper bound, i.e. \( R_{\text{upper}} \). Obviously, \( R_{\text{upper}} \) is given by

\[ R_{\text{upper}} = P(H_0)C_0 + P(H_1)C_1. \]  

(9)

Thus, the normalized throughput \( R_{\text{avg}} \) of SU-P and the traditional SU are plotted versus the traffic intensity \( \rho \), as shown in Fig. 3. Theoretical results are obtained according to the approach proposed in Section III. The simulated results are obtained using 20000 Monte-Carlo simulations which implement on the redesigned frame structure. It is observed that the theoretical and simulated results match well for all the three cases. Thus, in the subsequent figures, we will only show the theoretical results. We can also see that the SU-P’s normalized throughput outperforms the traditional SU’s, when the probability of wrong prediction \( P_{p}^w \) is 0.05 and 0.2. The results illustrate that SU-P’s normalized throughput is significantly improved. This is because the probability of waiting

### Table IV

<table>
<thead>
<tr>
<th>Parameter Setting</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target probability of detection ( P_d )</td>
<td>0.9</td>
</tr>
<tr>
<td>Target probability of false alarm ( P_f )</td>
<td>0.1</td>
</tr>
<tr>
<td>Frame duration ( T )</td>
<td>100 ms</td>
</tr>
<tr>
<td>Spectrum prediction duration ( \tau_p )</td>
<td>5 ms</td>
</tr>
<tr>
<td>Spectrum sensing duration ( \tau_s )</td>
<td>2.5 ms</td>
</tr>
<tr>
<td>Sampling frequency ( f_s )</td>
<td>1500 samples/s</td>
</tr>
<tr>
<td>SNR of SU at receiver ( SNR_s )</td>
<td>20 dB</td>
</tr>
<tr>
<td>SNR of PU at receiver ( SNR_p )</td>
<td>-15 dB</td>
</tr>
</tbody>
</table>

Fig. 2. Normalized throughput vs traffic intensity. (\( N = 10 \)).

Fig. 3. Normalized throughput vs traffic intensity. (\( N = 10 \)).
throughput. Therefore, it is further observed that the gap between SU-P’s normalized throughput and traditional SU’s becomes larger as the traffic intensity increases. This is because the traditional SU’s normalized throughput decreases as the increase of traffic intensity, while selecting an idle channel for sensing makes SU-P insensitive to the increase of the traffic intensity. However, since the probability of all channels predict to be busy can’t be ignored when the traffic intensity \( \rho \) is extremely high, SU-P’s normalized throughput decreases obviously. Moreover, it is observed that the performance of the normalized throughput when \( P_e^P = 0.05 \) outperforms that when \( P_e^P = 0.2 \), the reason lies in that more prediction errors lead to higher probability of selecting busy channels.

Fig. 4 shows the relationship between the SU-P’s normalized throughput \( R_{\text{norm}} \) and the probability of wrong prediction \( P_e^P \), and the normalized throughput of traditional SU is also shown for comparison, where the channel number \( N = 10 \). It can be observed that the gap between the normalized throughput of SU-P and the traditional SU becomes smaller as the probability of wrong prediction \( P_e^P \) increases. Considering prediction is useless when \( P_e^P = 0.5 \) and prediction occupies part of the frame duration, the SU-P’s normalized throughput is lower than the traditional SU’s when \( P_e^P = 0.5 \). Furthermore, it can be observed that the gap between the normalized throughput of SU-P and that of traditional SU becomes larger as the traffic intensity increases, which indicates that SU-P is more suitable for high traffic CRN.

The maximum normalized throughput \( R_{\text{norm}} \) and corresponding traffic intensity \( \rho \) for different channel number \( N \) are plotted in Fig. 5, where the probability of wrong prediction \( P_e^P = 0.05 \). It can be seen that the normalized throughput \( R_{\text{norm}} \) increases steadily as the channel number \( N \) increases, while the corresponding traffic intensity decreases simultaneously. This is because the number of channels predicted to be idle \( k \) increases as the channel number \( N \) increases, which lead to the increase of the probability of transmission and the improvement of SU-P’s normalized throughput. In addition, we can observe that the corresponding traffic intensity becomes lower when the maximum normalized throughput achieved, indicating that the normalized throughput \( R_{\text{norm}} \) increases faster as the channel number \( N \) increases. In a word, more channels are beneficial to improve SU-P’s throughput.

V. CONCLUSION

This letter investigate SU’s throughput enhancement from the perspective of improving sensing channel selection. SU’s frame structure is redesigned and applied spectrum prediction for selecting sensing channel from channel predicted to be idle. It can be observed that SU’s throughput enhanced evidently from numerical results. Furthermore, the impacts of the traffic intensity, the prediction error and the channel number on SU’s throughput are also evaluated.

REFERENCES