Capacity Impact of Location-aware Cognitive Sensing

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***Abstract*— We study Bayesian detection based cognitive sensing and analyze its impact on the capacity in various cases of location information. In a network of one primary and one cognitive users, the cognitive transmitter relies on information about the locations of the primary transmitter and the two receivers to design its optimal sensing threshold. Results show that this location-aware threshold can significantly improve the cognitive user's capacity, while imposing almost no detrimental effect on the primary user's capacity. Combined with à priori knowledge of the primary transmission probability, the location information is shown to be beneficial to the cognitive user's capacity when the primary user is likely to be active. Without the knowledge of the primary transmission probability, location information is beneficial for all range of primary activity.**

I. Introduction

The increasingly demanding communication requirements of higher speed and more versatile services put great pressure on the already crowded frequency spectrum. However, extensive research work [3], [4] shows that this pressure is mostly due to the currently inflexible frequency management, which results in some licensed spectrum significantly under-utilized, rather than an actual resource scarce. Based on these findings, cognitive radio systems, which allow one or more secondary users to access the licensed spectrum during idle time, provide a promising perspective to enhancing network capacities [6]. *Opportunistic spectrum access* is investigated in [5]. In this process, the cognitive users should decide whether and how to access a certain licensed spectrum. Intelligent detection decision for the cognitive user has important influence on the desired cognitive radio system goal, such as maximizing the capacity of cognitive users while creating negligible interference to the primary user. A popular method is to detect primary user transmission energy. Bayesian framework, which is usually used to design dynamic optimal threshold, has been widely applied to sequential detection problem in digital communication systems [7], to target tracking in wireless sensor networks [10] and pattern recognition [8]. Furthermore, the decision strategy in cognitive radio system can use different side information, including the primary coding scheme, channel condition, spatial locations, or their combinations [6], to enhance the sensing performance. In this paper, we focus on investigating the benefits of using radio location information on the decision rules and the network capacity.

In [2], the authors design optimal detection thresholds for the cognitive user utilizing spatial side information. Though the result shows that location information can be helpful to minimizing the detection cost, it does not give insight to the impact on the capacity of the users.

In this paper, we also formulate the cognitive sensing risk function based on Bayesian criterion [1], with the costs of miss-detection and false-alarm set as the interference and received signal powers. These interference and signal powers also affect the capacities. By minimizing this risk function, we derive the optimal sensing threshold for the secondary user in various cases of location side information. These cases include the cognitive transmitter having complete location information (i.e. it knows the locations of all other nodes in the network), partial location information and no location information. The location information is considered with and without the à priori knowledge of the primary transmission probability. Numerical results show that the location side information can greatly enhance not only the sensing risk performance but also the cognitive user capacity, while bringing little harm to the primary user capacity.

The paper is organized as follows. In Section II, we introduce the two-user network model and the channel model. In Section III, we quantify the sensing objective by introducing different location information sets and the *risk* function. In Section IV, we formulate the network capacity for both the primary and cognitive users. In Section V, we derive the optimal threshold for different location information cases and introduce the capacity computation methods. We discuss the numerical results in Section VI. Finally, we provide our concluding remarks in Section VII.

II. Network and Channel Models

A. Network Model

Consider a network consisting of one cognitive user and one primary user, each has a pair of transmitter and receiver which are randomly located. The location randomness can arise from mobility or from the random network access. Let the cognitive transmitter S_t be the center of the network at the polar coordinates $(0, 0)$. The cognitive receiver S_r is uniformly distributed within the disc centered at the origin with radius R_c. Let the impact radius of the cognitive transmitter be R_i such that any primary receiver falling within this radius will be noticeably interfered by the cognitive transmitter. The considered primary receiver P_r lies uniformly within this radius R_i. Centered at P_r, the primary transmitter P_t is uniformly distributed within the disc with radius R_p (see Fig. 1). The radii R_c, R_i and R_p are known network parameters. Furthermore, P_t P_r and C_r are used to specify the locations of P_t, P_r and S_r within the polar coordinates, respectively.

We assume a protected region around every receiving node, defined as a disc centered at this node which plays the receiver

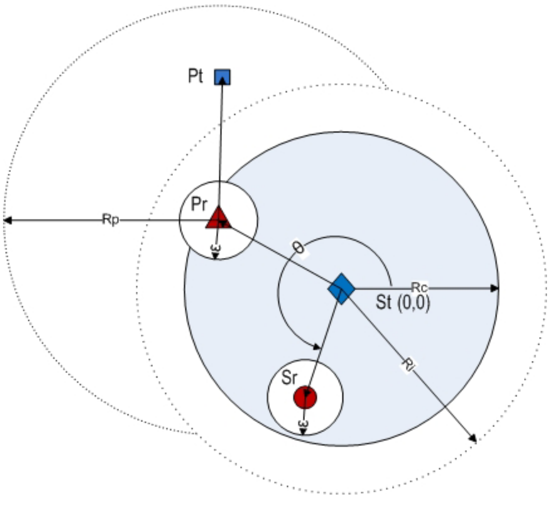

Fig. 1. Network model.

role. Any active transmitter cannot be inside this region to exclude the possibility that the receive signal and interference power rises to infinity. In Fig. 1, the circles centered at the receivers radios with radius ϵ are the protected regions.

Consider the cognitive receiver S_r. Let r and θ denote the radius and the angle of S_r in the polar coordinate. For uniformly distributed S_r, r has the probability density function:

$$f_r(r) = \frac{2r}{R_c^2 - \epsilon^2}\,, \qquad \epsilon \le r \le R_c.$$

and θ is uniform between 0 and 2π. The distributions for the radius and angles of P_r and P_t can be similarly derived.

B. Signal and Channel Models

Consider a wireless channel model with both large scale-path loss and small-scale fading. Free-space path loss h_{PL} models the averaged power changing with distance. Rayleigh fading h_{FD} is adopted for small-scale variation. The channel model between any Tx-Rx pair can then be written as follows

$$h = h_{PL} \cdot h_{FD} \tag{1}$$

where $h_{FD} \sim \mathcal{CN}(0, 1)$ is a complex circular Gaussian random variable with independent real and imaginary parts with equal variance; and

$$h_{PL} = \frac{A}{d^{\alpha/2}}$$

where A is a constant dependent on the frequency and transmitter/receiver antenna gain, and α is the pathloss exponent.

To sense the primary transmission, the cognitive transmitter needs to perform a hypothesis testing to decide between the following two hypotheses:

$$\mathcal{H}_0 : y = z \tag{2}$$

$$\mathcal{H}_1 : y = x + z \tag{3}$$

where y is the received samples at the cognitive Tx, $x \sim \mathcal{CN}(0, \sigma_x^2)$ is the signal received at the cognitive Tx from the primary Tx after experiencing path loss and fading, and $z \sim \mathcal{CN}(0, \sigma_z^2)$ is the thermal noise. Based on the channel model (1), $\sigma_x^2 = \mu h_{PL}^2$ where μ is the primary transmit power.

III. Sensing Objective

A. Location Information

In our model, the cognitive transmitter performs the detection the primary signal. Only when the cognitive transmitter detects that there is no primary transmission, it will begin its own transmission. We consider energy detection based on a Bayesian criterion.

Our goal is to use location information known to the cognitive transmitter to bolster cognitive sensing performance. This performance is defined in terms of a risk function for the Bayesian criterion, as specified below. Based on information about the node locations, the secondary transmitter can adjust its sensing threshold accordingly.

We investigate 4 following cases of location information:

- Case 1: S_t knows P_t, P_r and S_r
- Case 2: S_t knows P_r, S_r
- Case 3: S_t only knows S_r
- Case 4: S_t has no location information

These cases are chosen based on the fact that the location of the receivers are more important in assessing the interference and received signal.

In all the four cases, we assume that σ_x^2 and σ_z^2 are known, as these values can be estimated from stored sampled received signals. Although under this assumption, based on the channel model, the cognitive transmitter may be able to use σ_x^2 to deduce its distance to the primary transmitter, it cannot deduce the the primary transmitter's angle coordination and hence, cannot know the primary transmitter's location precisely. The knowledge of this distance alone can also alter the distributions of the locations of other nodes, making it difficult to analytically quantify the gain from this distance information. Thus, in this paper, we assume that the secondary transmitter does not use σ_x^2 to infer the distance to the primary transmitter.

B. Objective Risk Function

Using Bayesian criterion, the sensing objective is defined in term of a *risk* function involving the *miss detection* and *false alarm* probabilities as follows:

$$\Re = R_m \Pr(H_0|H_1, \gamma)\lambda_1 + R_f \Pr(H_1|H_0, \gamma)(1 - \lambda_1) \tag{4}$$

where

- λ_1 is the transmission probability of the primary user.
- γ is the sensing threshold.
- $\Pr(H_0|H_1, \gamma)$ is the miss-detection probability, when the secondary transmitter makes a decision to transmit while the primary transmitter is also active.
- R_m is the cost associated with miss-detection. Since both links will interfere each other, R_m can be set as

$$R_m = \beta(\bar{I}_{pc} + \bar{I}_{cp}) \tag{5}$$

where $\beta \geqslant 1$ is the penalty parameter to place a higher priority on primary user link, and $\bar{I}_{pc}$ ($\bar{I}_{cp}$) is the interference power, averaged over fading, from the cognitive (primary) user to the primary (cognitive) user (respectively).

- $\Pr(H_1|H_0,\gamma)$ is the false-alarm probability, when the secondary transmitter makes a decision not to transmit while the primary link is idle.
- R_f is the cost associated with false alarm. The secondary user then misses its chance to achieve a higher capacity, thus R_f can be set as the average power $\bar{L}_c$ received by the secondary receiver

$$R_f = \bar{L}_c. \tag{6}$$

Taking into account the random locations of the transmitters and receivers, the risk in (4) can then be written as

$$\Re = E_{S_t,S_r,P_t}\Big[\beta(\bar{I}_{pc}+\bar{I}_{cp})Pr(H_0|H_1,\gamma)\lambda_1 + \bar{L}_c Pr(H_1|H_0,\gamma)(1-\lambda_1)\Big]. \tag{7}$$

The sensing threshold will be designed to minimize this risk in the different cases of location information.

IV. Capacity Formulation

The sensing decision of the cognitive user influences the capacity of both the primary and cognitive users. *Miss detection* will cause interference to both users, while *false alarm* will waste precious spectrum in the idle time, jeopardizing the network throughput (sum capacity). In addition, the users' capacities are also affected by the transmission probability of the primary user. Taking all these elements into account, we can formulate the averaged capacities of primary and cognitive link rates as follows

$$C_p = E_{S_r,P_r,P_t}\left\{\Pr(H_1|H_1,\gamma)\lambda_1 E\left[\log_2\left(1+\frac{L_p}{\sigma_z^2}\right)\right] + \Pr(H_0|H_1,\gamma)\lambda_1 E\left[\log_2\left(1+\frac{L_p}{\sigma_z^2+I_{pc}}\right)\right]\right\} \tag{8}$$

$$C_c = E_{S_r,P_r,P_t}\left\{\Pr(H_0|H_0,\gamma)(1-\lambda_1) E\left[\log_2\left(1+\frac{L_c}{\sigma_z^2}\right)\right] + \Pr(H_0|H_1,\gamma)\lambda_1 E\left[\log_2\left(1+\frac{L_c}{\sigma_z^2+I_{cp}}\right)\right]\right\} \tag{9}$$

where L_p and L_c are the random received signal power at the primary and cognitive receiver, and I_{pc} and I_{cp} are the corresponding random interference power. The innermost expectation is performed over fading. After deriving the optimal threshold, we will analyze how the sensing decision in different location information cases affect the capacities.

V. Optimal Threshold

In this section, we derive the optimal thresholds to minimize the *risk* in (7) for different cases of location information. In these derivations, we assume that the cognitive transmitter knows à priori the primary transmission probability λ_1. When the primary transmission probability is unknown, the optimal threshold is obtained by setting $\lambda_1 = 0.5$ in the corresponding case.

A. Case 1: When P_r, S_r and P_t are known

With all location information, minimizing (7) is equivalent to minimizing the risk for each specific set of locations P_r, S_r and P_t:

$$\Re_0 = \beta(\bar{I}_{pc}+\bar{I}_{cp})\Pr(H_0|H_1,\gamma)\lambda_1 + \bar{L}_c\Pr(H_1|H_0,\gamma)(1-\lambda_1). \tag{10}$$

Taking into account the complex Gaussian distribution of the received signal y in both hypotheses (2) and (3), the optimal decision rule is [2]:

$$\frac{\beta(\bar{I}_{pc}+\bar{I}_{cp})\Pr(|y||H_1)\lambda_1}{\bar{L}_c\Pr(|y||H_0)(1-\lambda_1)} \mathop{\gtrless}_{H_0}^{H_1} 1$$
$$\Longleftrightarrow \frac{\frac{2|y|}{\sigma_x^2+\sigma_z^2}e^{-\frac{|y|^2}{\sigma_x^2+\sigma_z^2}}}{\frac{2|y|}{\sigma_z^2}e^{-\frac{|y|^2}{\sigma_z^2}}} \mathop{\gtrless}_{H_0}^{H_1} \frac{1-\lambda_1}{\lambda_1}\frac{\bar{L}_c}{\beta(\bar{I}_{pc}+\bar{I}_{cp})} \tag{11}$$

Thus the optimal threshold to be compared with the received signal power can be computed as

$$|y|^2 \mathop{\gtrless}_{H_0}^{H_1} \gamma_1 = \frac{\sigma_z^2}{\sigma_x^2}(\sigma_x^2+\sigma_z^2)\left[\ln\left(1+\frac{\sigma_x^2}{\sigma_z^2}\right)+\ln\left(\frac{1-\lambda_1}{\lambda_1}\right) + \ln\left(\frac{\bar{L}_c}{\beta(\bar{I}_{pc}+\bar{I}_{cp})}\right)\right]$$

For some set of locations, γ_1 can be negative, implying that S_t always cannot transmits. Thus the optimal threshold can be written as $\gamma = \max(0,\gamma_1)$.

In this case, as the cognitive transmitter know the location of all other nodes, the capacities can be calculated explicitly for each set of locations and then averaged over all the locations as in (8) and (9).

B. Case 2: When P_r and S_r are known

Since S_t has no knowledge of S_{ptx}, it should design the threshold based on the risk averaged over S_{ptx} for each pair of $\{S_{crx}, S_{prx}\}$. Minimizing (7) is equivalent to minimizing

$$\Re_1 = \beta(\bar{I}_{pc}+E_{P_t}[\bar{I}_{cp}])\Pr(H_0|H_1,\gamma)\lambda_1 + \bar{L}_c\Pr(H_1|H_0,\gamma)(1-\lambda_1)$$

The optimal threshold can be derived as $\gamma = \max(0,\gamma_2)$ where

$$\gamma_2 = \frac{\sigma_z^2}{\sigma_x^2}(\sigma_x^2+\sigma_z^2)\left[\ln\left(1+\frac{\sigma_x^2}{\sigma_z^2}\right)+\ln\left(\frac{1-\lambda_1}{\lambda_1}\right) + \ln\left(\frac{\bar{L}_c}{\beta(\bar{I}_{pc}+E_{P_t}[\bar{I}_{cp}])}\right)\right] \tag{12}$$

The respective primary and cognitive link rates are calculated as follows.

$$C_p = E_{S_r,P_r}\left[\Pr(H_1|H_1,\gamma)\lambda_1 E_{P_t}\left\{E\left[\log_2\left(1+\frac{L_p}{\sigma_z^2}\right)\right]\right\} + \Pr(H_0|H_1,\gamma)\lambda_1 E_{P_t}\left\{E\left[\log_2\left(1+\frac{L_p}{\sigma_z^2+I_{pc}}\right)\right]\right\}\right]$$

$$C_c = E_{S_r,P_r,P_t}\left[\Pr(H_0|H_0,\gamma)(1-\lambda_1)E\left[\log_2\left(1+\frac{L_c}{\sigma_z^2}\right)\right]\right]$$
$$+E_{S_r,P_r}\left[\Pr(H_0|H_1,\gamma)\lambda_1 E_{P_t}\left\{E\left[\log_2\left(1+\frac{L_c}{\sigma_z^2+I_{cp}}\right)\right]\right\}\right]$$

C. Case 3: When only S_r is known

Similar to Case 2, since S_t does not know P_t and P_r, the average interference power and received signal power in the threshold should be averaged over all $\{P_t, P_r\}$ for each given S_r. The optimal threshold in this case is $\gamma = \max(0, \gamma_3)$ where

$$\gamma_3 = \frac{\sigma_z^2}{\sigma_x^2}(\sigma_x^2+\sigma_z^2)\left[\ln\left(1+\frac{\sigma_x^2}{\sigma_z^2}\right)+\ln\left(\frac{1-\lambda_1}{\lambda_1}\right)\right.$$
$$\left.+\ln\left(\frac{\bar{L}_c}{\beta(E_{P_r,P_t}[\bar{I}_{pc}]+E_{P_r,P_t}[\bar{I}_{cp}])}\right)\right]$$

The respective capacity should be calculated as

$$C_p = E_{S_r}\left[\Pr(H_1|H_1,\gamma)\lambda_1 E_{P_r,P_t}\left\{E\left[\log_2\left(1+\frac{L_p}{\sigma_z^2}\right)\right]\right\}\right.$$
$$\left.+\Pr(H_0|H_1,\gamma)\lambda_1 E_{P_r,P_t}\left\{E\left[\log_2\left(1+\frac{L_p}{\sigma_z^2+I_{pc}}\right)\right]\right\}\right]$$
$$C_c = E_{S_r,P_r,P_t}\left\{\Pr(H_0|H_0,\gamma)(1-\lambda_1)E\left[\log_2\left(1+\frac{L_c}{\sigma_z^2}\right)\right]\right\}$$
$$+E_{S_r}\left[\Pr(H_0|H_1,\gamma)\lambda_1 E_{P_r,P_t}\left\{E\left[\log_2\left(1+\frac{L_c}{\sigma_z^2+I_{cp}}\right)\right]\right\}\right]$$

D. Case 4: When no location information is known

As S_t has no location information, the interference power and received signal power in the threshold should be averaged across all locations. The optimal threshold is given as $\gamma = \max(0, \gamma_4)$ where

$$\gamma_4 = \frac{\sigma_z^2}{\sigma_x^2}(\sigma_x^2+\sigma_z^2)\left[\ln\left(1+\frac{\sigma_x^2}{\sigma_z^2}\right)+\ln\left(\frac{1-\lambda_1}{\lambda_1}\right)+\right.$$
$$\left.\ln\left(\frac{E_{S_r,P_r,P_t}[\bar{L}_c]}{\beta(E_{S_r,P_r,P_t}[\bar{I}_{pc}]+E_{S_r,P_r,P_t}[\bar{I}_{cp}])}\right)\right] \quad (13)$$

The respective primary and cognitive link rates can be calculated according to (8) and (9).

E. Multiple Cognitive User

In a cognitive network, there may be n cognitive users who wish to access a certain frequency during idle times. The proposed sensing algorithms can be extended to this case in a distributed manner. Each cognitive user only needs to use local information on the locations of its own receiver and the primary transmitter and receiver. The interference from other cognitive users can be treated as noise as follows. To account for the fact that not all cognitive users may be active at the same time, we can introduce an active factor $\delta < 1$, such that the number of cognitive user concurrently transmitting is δn. The specific δ value can be obtained through analytical modeling or simulation. Then, provided that all cognitive users have the same spatial distribution, a cognitive transmitter can compute the average interference power from other active cognitive users and treat that as additional noise in its optimal threshold calculation.

VI. Numerical Results

A. Simulation Methods

For the simulations, we use the model in Fig. 1 and set the network radii $R_c = R_p = R_i = 10$, the protection region $\epsilon = 1$ and the pathloss parameter $\alpha = 2.1$. The primary and secondary transmit power and the thermal noise are set such that at the edge of a disc, the SNR is 0dB. For Case 1, we first generate 3000 sets of locations P_t, P_r and S_r. For each set, 10000 Rayleigh fading channels are generated per link. We then compute the optimal threshold for each set of locations, perform detection and compute the risk and capacities. The risk and capacities are then averaged over fading and the different locations.

For Case 2, since P_t is unknown, 3000 sets of P_r and S_r are generated first. Then for each pair of $\{P_r, S_r\}$, another 3,000 P_t are generated to compute the averaged interference and received power in the threshold (12). After obtaining the threshold for each set of locations, the same number of Rayleigh fading channels as in Case 1 are generated to perform the detection. Then the program computes the primary and cognitive capacities averaged over fading and P_t, given the specific pair $\{P_r, S_r\}$. In the last step, these capacities are averaged over all $\{P_r, S_r\}$ pairs.

For Case 3, we use the same methodology and the same parameters as in Case 2. For Case 4, since the cognitive transmitter has no location information, the random locations of P_t, P_r and S_r can be generated in the same way as Case 1. The average interference power $\bar{I}_{pc}$ and link quality power $\bar{L}_c$ in the threshold (13) can be calculated analytically and the average interference power $\bar{I}_{cp}$ is computed numerically.

B. Results and Discussion

1) The sensing risk function: In Fig. 2, we plot the risks as a function of λ_1 for all cases of location information without knowing λ_1. The plot shows that location information improves the sensing performance: the detection is best when S_t has all location information and is worst when it has no location information. The improvement is quite significant. Just a single piece of information on S_r can reduce the sensing risk by about 40%, while all location information can reduce the risk by up to 60% at low λ_1.

Fig. 3 shows similar results when S_t knows λ_1. We observe the same effect of location information on sensing performance: more information is helpful. The prior knowledge of λ_1 also helps to further reduce the sensing risk. The impact of knowing λ_1 increases as $|\lambda_1 - 0.5|$ increases.

2) Capacities with $\beta = 1$: By setting $\beta = 1$ in (5), we place little penalty on the cognitive user for interfering with the primary user. In Fig. 4, we plot the capacities of both the primary and cognitive users for the cases without knowing λ_1. The results show that the more location information the cognitive user can obtain, the higher capacity this user can achieve, while bringing little harm to the primary user. This is a quite encouraging result. Location information is a beneficial factor to the cognitive user's capacity in this case.

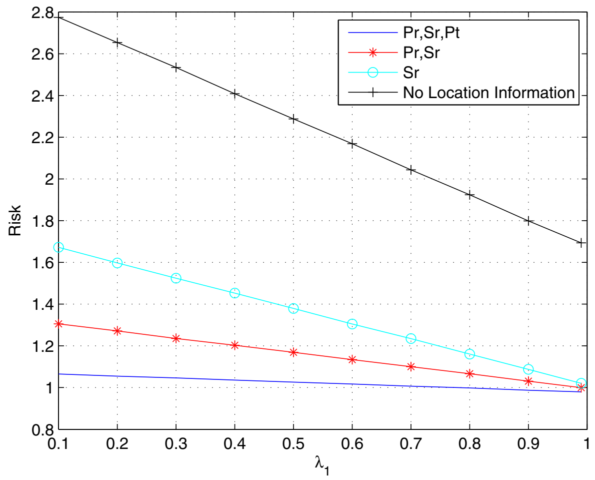

Fig. 2. Detection risk without the knowledge of λ_1.

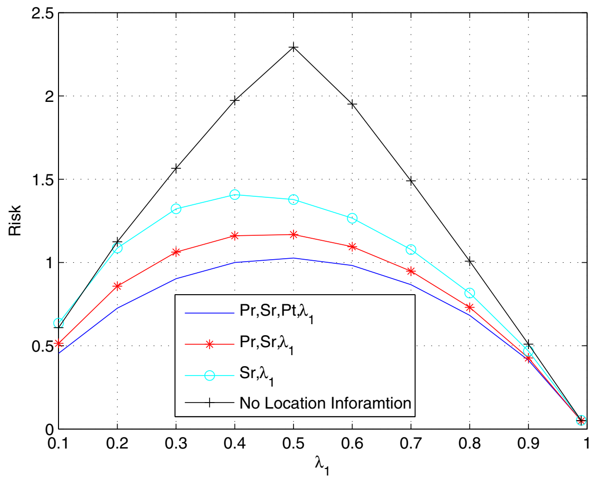

Fig. 3. Detection risk with the knowledge of λ_1.

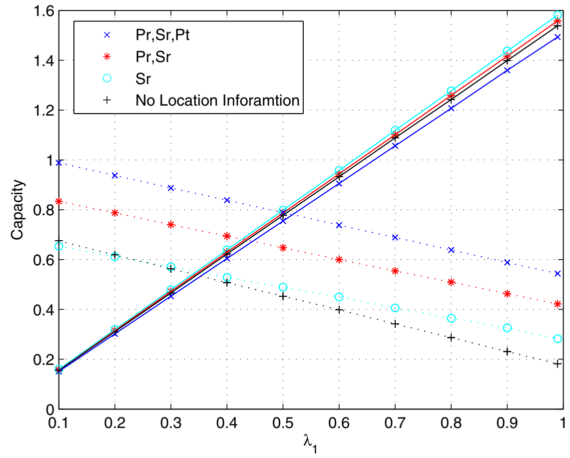

Fig. 4. Primary (solid lines) and cognitive (dotted lines) capacities without the knowledge of λ_1 ($\beta = 1$).

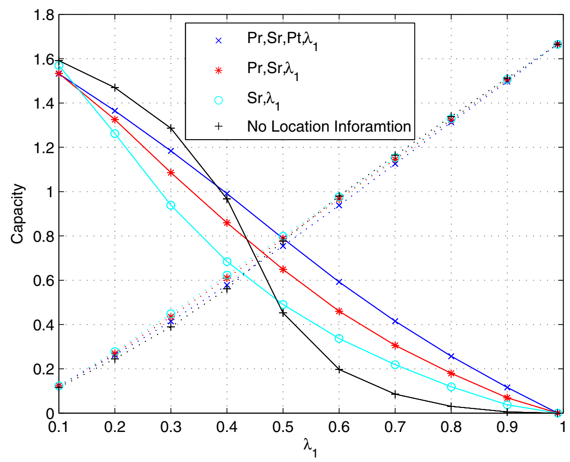

Fig. 5. Primary (dotted lines) and cognitive (solid lines) capacities with the knowledge of λ_1 ($\beta = 1$).

With the knowledge of λ_1, however, a different picture emerges, as shown in Fig. 5. While the capacity of the cognitive user in Case 1, 2 and 3 follows a decreasing order for all values of λ_1 as expected, the capacity in Case 4 has an unexpected twist at $\lambda_1 < 0.5$. For $\lambda_1 < 0.5$, the cognitive user's capacity without any location information rises above the other cases with location information. A closer look at the simulations reveals that, in Case 4, for $\lambda_1 < 0.5$, the threshold is much larger than the mean receive signal power in every location and the cognitive user always transmits. So in this case, the cognitive transmitter relies solely on the information about λ_1 to set its threshold. Quite surprisingly, this aggressive cognitive transmission affects the primary user very little, because of the small primary transmission probability in this region. The primary user's capacity is about the same in all cases of cognitive location information.

3) Capacities with $\beta = 5$: As in Fig. 4, the primary user still suffers a modest reduction in capacity with increasing cognitive information, we are motivated to study the case when the cognitive user is more heavily penalized for interfering with the primary user. This is done by setting $\beta = 5$, placing more penalty when the cognitive user miss-detects. Simulation results for the case without knowing λ_1, while not shown here, show that while $\beta = 5$ helps to keep the primary user's capacity almost the same in all cases with a slight increase compared to when $\beta = 1$, the cognitive user's capacity drops dramatically, by about 40% to 80%, depending on the location information. Thus higher penalty on the cognitive user's interference is actually not beneficial here.

Fig. 6 shows cognitive capacities when λ_1 is known. The primary user's capacities are of the same magnitudes as for $\beta = 1$ and are not shown here. For the cognitive user, the knowledge of λ_1 helps improve the capacity when $\lambda_1 < 0.5$, but this effect disappears when $\lambda_1 > 0.5$. Location information, on the other hand, improves the cognitive capacity for

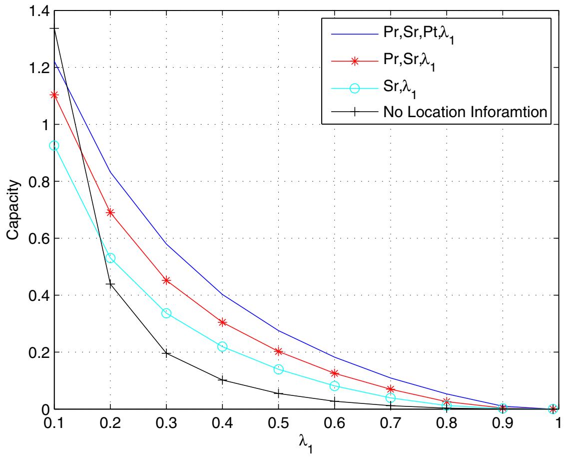

Fig. 6. Cognitive capacities with the knowledge of λ_1 ($\beta = 5$).

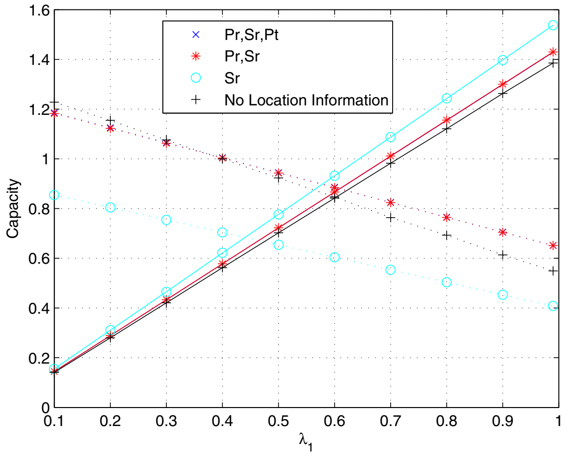

Fig. 7. Primary (solid lines) and cognitive (dotted lines) capacities with different location information without the knowledge of λ_1 plotted using thresholds in [2].

almost all values of λ_1. Again, similar to Fig. 5, we observe that the cognitive user's capacity is higher in case 4 than the other three, although this occurs only at $\lambda < 0.2$ rather than at $\lambda < 0.5$. Thus increasing the penalty factor β makes the cognitive user to be more reserve in its transmission, therefore location information is beneficial for a larger range of λ_1.

4) The importance of selecting the Bayesian cost functions: With the Bayesian criterion (4), in order for the benefit of location information to also be reflected in the capacity, it is crucial to select suitable functions for the cost of miss-detection (5) and false-alarm (6). In Fig. 7, we show the primary and cognitive users' capacities with the threshold design in [2], which employed a different function for the miss-detection cost that included only the interference to the primary receiver. The capacities for case 1 and case 2 are then the same, since the location of the primary transmitter has no affect on the cost. For the primary user's capacity suffers more loss than using our proposed threshold in Fig. 4. Moreover, for the cognitive user, the capacity without any information is actually higher than that with S_r. Thus while the location information merits are reflected through the Bayesian risk function as shown in [2], it is not revealed in the capacity.

VII. Conclusion

We have considered cognitive sensing with the aim of minimizing the interference to the primary user and maximizing the cognitive user's spectrum access agility. We first analytically derive the optimal sensing threshold to minimize the detection risk, utilizing available location side information and à priori primary transmission probability. We then investigate the network capacity with the different sets of side information. We observe that when the cognitive transmitter knows the complete locations of other nodes and the primary transmission probability, its detection performance is the best. When the primary transmission probability deviates from 0.5, its à priori knowledge helps the cognitive transmitter to more accurately access the spectrum idle time. Simulation results also show that, with suitably chosen Bayesian cost functions, location side information can also significantly increase the cognitive user's capacity while bringing little harm to the primary user's capacity. In low primary transmission region, the knowledge of primary activity has strong impact on increasing the cognitive user's capacity. But its impact decreases as the primary transmission probability goes higher, while the location information advantages become more explicitly revealed. Furthermore, it is discussable whether or not to exert more penalties to the miss detection behavior, for the fact that the cognitive capacity deterioration is much higher than the primary capacity enhancement benefiting from the cognitive user's modesty.

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