Transmitter-Receiver Cooperative Sensing in MIMO Cognitive Network with Limited Feedback

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***Abstract*—In this paper, we proposed a novel sensing scheme so-called Transmitter-Receiver Cooperative Sensing in a MIMO cognitive network by combining sensing information of both sides. Compared with most of the existing sensing schemes which simply use listen-before talk (LBT) only at the transmitter side, the proposed scheme can further improve the system performance by jointly feedback the Channel State Information (CSI) and the Sensing information (SI) from the receiver. However, the quantization impact on the sensing performance and the channel capacity as well as the interference to primary network should be considered in the case of limited feedback. Here a tradeoff criterion is proposed to allocate bits for CSI and SI so as to maximize the MIMO link capacity while meeting the interference constraints. Simulation results are given to verify the effectiveness of the proposed scheme.**

I. Introduction

During the recent years, with the establishment of the new communication systems like LTE and LTE-Advanced, the requirement of spectrum has increased tremendously. On the contrary, the lack of spectrum resources becomes an urgent problem. It is obvious that the current static spectrum allocation schemes can not afford the requirements of an increasing number of higher date rate devices. Under these circumstances, *cognitive radio* is invited to be a solution to the spectrum problem by opportunistically accessing the spectrum which originally authorized to the primary network but without heavily occupying [1] [2]. From the conception of the cognitive networks, the spectrum is occupied by two kinds of users with different priorities. One is called the primary users which have higher priority to access the channel. The other is secondary users which have lower priority to access the channel. The secondary users should have the cognitive ability to protect the primary users from being interfered.

One of the key technique in cognitive radio is sensing. With the help of sensing results, the secondary users could be aware of the activity of the primary user as well as the parameters related to the channel characteristics. Then the secondary users could opportunistically access the spectrum which has been authorized to the primary network without causing any interference. Therefore, spectrum sensing is the most important component of the cognitive network, it has been well studied in the past decade. Most of the issues about spectrum sensing are summarized in [3] and [4]. However, the sensing performance of a single secondary user is limited because of the channel fading and the shadowing. To meet the requirement of enhancing the sensing ability of the secondary users, a cooperative sensing scheme has attracted considerable attention[5] [6]. Cooperative sensing is proposed in the previous literature as a solution to problems that arise in spectrum sensing due to noise uncertainty, fading, and shadowing. It also decreases the probabilities of miss- detection and false alarm considerably.In the cooperative approach, each secondary user senses independently and then exchanges the local information to make a global decision. From 1-bit decision fusion[7] to soft data fusion[8], the schemes of the local information fusion have also been studied in many literatures.

In the previous works, cognitive radio in conjunction of multi-antenna technique has attracted considerable attention. With the help of exploiting spatial degrees of freedom, multi-antenna technique could easily eliminate interference to the primary users and improve the performance of the secondary radio link[9]. One of the most important issue of multi-antenna system is the improvement of the channel capacity and link reliability. It is well known that with the channel state information(CSI) at the transmitter, the multi-antenna system could obtain considerable improvement in capacity or link reliability[10].

But in the multi-antenna cognitive network, alleviating the interference towards the primary users should be considered as first priority. Most of the sensing mechanisms based on simply LBT(listen-before talk) scheme only at the transmit side. MIMO cognitive network with feedback provides a natural cooperative environment. Under that circumstance, the information fusion at the transmit is made by considering the decisions of the transmit itself and the sensing results from the receiver.

The scheme of sending the cooperative information through the feedback channel is proposed in this paper. However, the quantization impact on both cooperative sensing and capacity of MIMO channel should be considered because the feedback channel is limited. And a tradeoff criterion is proposed to balance the performance of the cognitive radio link as well as the interference towards the primary networks.

The rest of this paper is organized as follows: Section II

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gives a brief introduction of the considered MIMO cognitive network. The impact of quantized feedback on both cooperative sensing and MIMO capacity are analyzed in Section III. Then a objective function is defined and a tradeoff strategy is proposed in Section IV.Several numerical results are presented in Section V and the whole paper is concluded in Section VI.

II. System Model

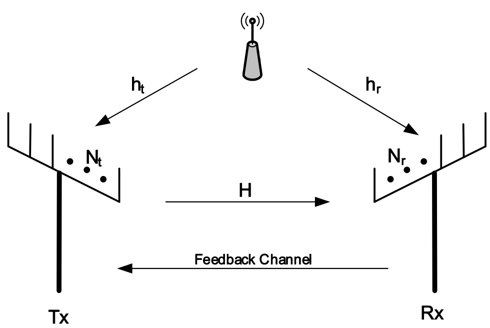

Fig. 1. An overview of the considered system model.

A. Channel Model

We consider a CR system model including two networks called primary and cognitive network, as seen in Fig.1. For cognitive network, Tx and Rx are equipped with N_t and N_r antennas respectively while the primary user has only one antenna. The channel from the primary transmit to the Tx and Rx are respectively denoted by $\mathbf{h}_t$, $\mathbf{h}_r$ with independent and identical distributed(i.i.d.) zero mean and unit variance Gaussian entries. The channel from the Tx to Rx is denoted by $\mathbf{H}$, where $\mathbf{H}$ is a N_t by N_r matrix with i.i.d. zero mean and unit variance Gaussian entries. It is assumed that the channels are quasi-stationary and ergodic which means the channel remains constant in a transmission block and independently fades block by block. In addition, there exists a feedback channel from the Rx to Tx with a limited capacity.

B. Primary Signal Model

The primary user is assumed to be either active or idle during the block. The hypotheses of the absence and presence of the primary user are denoted as $\mathcal{H}_0$ and $\mathcal{H}_1$ respectively. Throughout this article, we assume that the Tx and Rx has only one sensing result each. Because the antennas in one device are very close. The received signals are

$$r_i = \begin{cases} n_i & \mathcal{H}_0 \\ \sqrt{\gamma_i} s_i + n_i & \mathcal{H}_1 \end{cases} \tag{1}$$

where *i* is equal to *t* for the received signal at the Tx and *r* for the received signal at the Rx. $\sqrt{\gamma_i} s_i$ denotes the received primary signal with the average power γ_i and n_i denotes the white Gaussian noise. Without loss of generality, we assume that noise is Gaussian with zero mean and unit variance and s_i for different *i* are i.i.d. Gaussian random variables with zero mean and unit variance. According to the assumptions above, the received signal has the following distribution

$$r_i = \begin{cases} \mathcal{N}(0,1) & \mathcal{H}_0 \\ \mathcal{N}(0,1+\gamma_i) & \mathcal{H}_1 \end{cases} \tag{2}$$

C. Transmission Strategy

At the beginning of each transmission block, the Tx and Rx are using energy detector to sense the channel simultaneity. Then the Rx feeds two kinds of information back, one is the sensing information (SI) and the other is the channel state information (CSI). Then the Tx using the SI to decide whether to transmit the signals and using the CSI to do the precoding. Because the feedback bits are limited, the more bits used in the SI could obtain the activity of the primary user more precisely. On the other hand, more bits used in the CSI could enhance the performance of the cognitive link. As mentioned above, bit allocation between two kinds of information should be considered as a tradeoff strategy.

III. Quantization Impact on Sensing ability and Capacity

Before we allocate the bits between CSI and SI, the impact of quantization on both information should be analyzed first.

A. Quantization Impact on Sensing ability

According to (2), the energy detecting results is given by:

$$Y_i = r_i^2 = \begin{cases} R_{i0} & \mathcal{H}_0 \\ (1+\gamma_i)R_{i1} & \mathcal{H}_1 \end{cases} \tag{3}$$

where the random variance R_{i0} and R_{i1} follow a central chi-square distribution with one degree of freedom. We assume that Y_i are independent for given hypothesis because Tx and Rx are at different locations.

Without loss of generality, probability of detection P_D and probability of false alarm P_F are used for demonstrating the sensing ability. The P_D and P_F can be obtained from (3).

$$\mathrm{P}_D(\lambda) = \mathrm{P}(Y_i > \lambda \,|\mathcal{H}_1) = \frac{\Gamma\left(\frac{1}{2}, \frac{\lambda}{2(1+\gamma_i)}\right)}{\Gamma\left(\frac{1}{2}\right)} \tag{4}$$

and

$$\mathrm{P}_F(\lambda) = \mathrm{P}(Y_i > \lambda \,|\mathcal{H}_0) = \frac{\Gamma\left(\frac{1}{2}, \frac{\lambda}{2}\right)}{\Gamma\left(\frac{1}{2}\right)} \tag{5}$$

where λ is the decision threshold, $\Gamma(\cdot)$ and $\Gamma(\cdot,\cdot)$ denote the gamma function and upper incomplete gamma function, respectively.

When the sensing period is over, the Rx should feed its quantized sensing results back to Tx, we assume that the quantization function is $\mathbf{Q}[\cdot]$, so the P_D and P_F at the transmitter are

$$\mathrm{P}_D(\lambda') = \mathrm{P}(Y = Y_t + \mathbf{Q}[Y_r] > \lambda' \,|\mathcal{H}_1) \tag{6}$$

and

$$\mathrm{P}_F(\lambda') = \mathrm{P}(Y = Y_t + \mathbf{Q}[Y_r] > \lambda' \,|\mathcal{H}_0) \tag{7}$$

where λ' is the decision threshold after combination and $\mathbf{Q}[Y_r]$ is the quantized energy. The quantization function $\mathbf{Q}[\cdot]$ divided the received energy into 2^{B_S} different regions, where B_S is the number of bits used for quantizing SI.

Although the received energy follows the chi-square distribution, most of the energy located in the finite region, we assume that $E_{max}(P_{max})$ is the received energy which is larger than P_{max} percentage of the received energy. The quantization function $\mathbf{Q}[\cdot]$ divided E_{max} into 2^{B_S} regions uniformly. We have the following quantization function

$$\mathbf{Q}[Y_r] = q_j \tag{8}$$

$$if \qquad Y_r \in [\eta_{j-1}, \eta_j) \; j = 1 \ldots 2^{B_S}$$

where $\eta_0 = 0$, $\eta_{2^{B_C}} = E_{max}$ and $q_j = \frac{\eta_{j-1}+\eta_j}{2}$. For each region j, the probability of the energy located in region j is the same, we have

$$\int\limits_{\eta_{j-1}}^{\eta_j} p_{\chi^2}\left(x\right)dx = \frac{1}{2^{B_S}} \tag{9}$$

where $p_{\chi^2}(\cdot)$ is the probability distribution function of the chi-square distribution with one degree of freedom.

The signal energy Y follows a distribution with one central chi-square distribution variable plus one discrete variable. It has the following probability distribution function

$$p_Y\left(z\right) = \sum_{j=1}^{2^{B_S}} p_{\chi^2}\left(z - q_j\right)p_{q_j} \tag{10}$$

From the pdf of Y above, the P_D and P_F can be written as

$$\mathrm{P}_D\left(\lambda', B_S\right) = \mathrm{P}\left(Y > \lambda' \left|\mathcal{H}_1\right.\right) \tag{11}$$
$$\mathrm{P}_F\left(\lambda', B_S\right) = \mathrm{P}\left(Y > \lambda' \left|\mathcal{H}_0\right.\right) \tag{12}$$

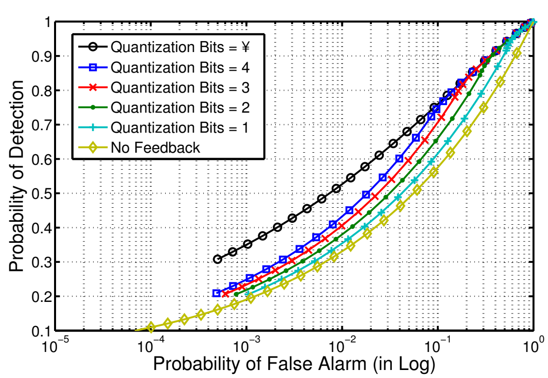

Fig. 2. Probability of detection and Probability of false alarm curves for different feedback bits.

Figure 2 shows the corresponding $P_D - P_F$ curves of different B_S, here we assume that $\gamma_t = \gamma_r = 5$dB and B_S chosen from 1 to 4. The cases of perfect feedback and no feedback are compared as well are shown for comparison. From figure 2, we can see that with the increasing of the quantization bits, the sensing ability is improved. Figure 2 also shows that the curves of limited feedback scheme is close to the curve of perfect feedback scheme when P_D is more than 0.7. In that situation, there is little benefit from increasing the feedback bits on SI.

In order to figure out the bound of sensing benefits from cooperation. The gap of P_F between perfect feedback scheme and no feedback scheme under certain P_D is shown in figure 3.

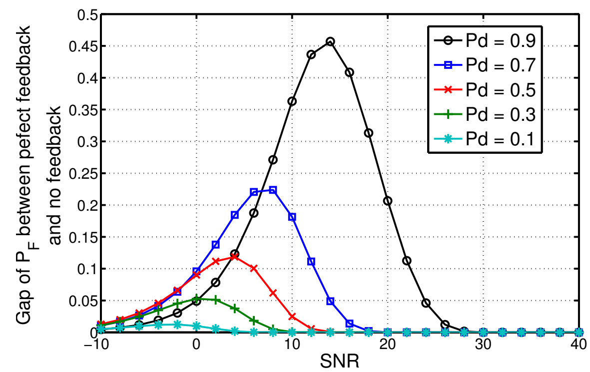

Fig. 3. Gap of P_F between Perfect feedback and No feedback in different SNRs.

The perfect feedback and no feedback scheme are the upper and lower bound of the limited feedback scheme, respectively. Hence, the larger the gap between them, more benefits can be obtained by increasing the number of bits on SI.

B. Quantization Impact on MIMO Capacity

Without loss of generality, we consider a codebook based feedback scheme because it has been well studied. The procedure is as following, the Rx selects the optimal beamformer $\mathbf{w}_i$ from a codebook $\mathcal{W}$ of size 2^{B_C}, where B_C is the number of bits used for quantizing CSI, then conveys the index i to the Tx. After beamforming using the corresponding beamformer, the received signal can be expressed as

$$\mathbf{y} = \mathbf{H}\mathbf{w}_i x + \mathbf{n} \tag{13}$$

where $\mathbf{y}$ is $N_r \times 1$ received signal and $\mathbf{n}$ is the $N_r \times 1$ received noise with zero mean and unit variance. We assume a MRC scheme is performed at the Rx, so the beamformer selection criteria is given by

$$i = \underset{1 \le i \le 2^{B_C}}{\arg\max} \left\|\mathbf{H}\mathbf{w}_i\right\|_2^2 \tag{14}$$

using eigenvalue decomposition(EVD), $||\mathbf{H}\mathbf{w}_i||_2^2$can be expressed as

$$\left\|\mathbf{H}\mathbf{w}_i\right\|_2^2 = \sum_{k=1}^{Ne} \lambda_k \left|\boldsymbol{\mu}_k^* \mathbf{w}_i\right|^2 \tag{15}$$

where N_e is the number of the nonzero eigenvalue of $\mathbf{H}^*\mathbf{H}$, λ_k and $\boldsymbol{\mu}_k$ are the kth eigenvalue and corresponding eigenvector, respectively. We assume that the eigenvalues are ranked in decreasing order and the beamformer selection criteria is to choose a beamformer has the largest correlation with $\boldsymbol{\mu}_1$ which

$$g(\Upsilon,B,N_t,N_r)=\frac{\eta}{\Upsilon}\sum_{m=0}^{N_t-2}(-1)^m\,\mathrm{C}_{\mathrm{N_t}-2}^{\mathrm{n_t}}\left((1-\kappa)^{m+1}\left|\Psi\left(\frac{\Upsilon}{1-\kappa}\right)\right|-\left|\Psi\left(\Upsilon\right)\right|+(m+1)\,M\left(m,\Upsilon\right)\right) \tag{17}$$

is the corresponding eigenvector to the largest eigenvalue λ_1. As a result, the other terms can be neglected as compared with the first one in the sum of (15). The effective channel gain is defined as

$$\Upsilon=\lambda_1\left|\boldsymbol{\mu}_1^*\mathbf{w}_i\right|^2 \tag{16}$$

We have the pdf of Υ from previous literature as (17) where $\kappa=\frac{\delta_{max}}{2}^2$,and $\delta_{max}\simeq 2\cdot 2^{-\frac{B_C}{2(N_t-1)}}$ is the maximum minimum distance of the codebook according to Grassmann manifold theory. And $\Psi\left(x\right)$ is a $s\times s$ matrix whose entries are given by

$$\left[\Psi\left(x\right)\right]_{i,j}=\gamma\left(t+s-i-j+1,x\right)$$

where $\gamma(\cdot,\cdot)$ is the incomplete gamma function and $t=min(N_t,N_r)$,$s=max(N_t,N_r)$. The η and $M(\cdot,\cdot)$ in (17) are given by

$$\eta=\frac{2^B\left(N_t-1\right)}{\prod_{k=1}^{s}\Gamma(t-k+1)\Gamma(s-k+1)}$$

$$M\left(m,\Upsilon\right)=\int_{1-\kappa}^{1}y^m\left|\Psi\left(\frac{\Upsilon}{y}\right)\right|dy$$

Throughout this article, we assume that N_t=3 and N_r=3 for convenience.

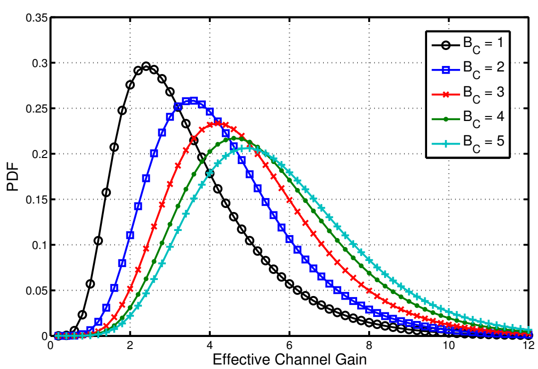

Fig. 4. PDF of the effective channel gain for different feedback bits.

Figure 4 shows the pdf of the effective channel gain for different numbers of feedback bits. We can see from the figure that with the more feedback bits, the probability of the large effective channel gain increases.

We assume that $C(B_C)$ is the capacity of the cognitive link which is defined as

$$C(B_C)=\mathbf{E}[g(\Upsilon)\log_2(1+\Upsilon)] \tag{18}$$

and the capacities of MIMO radio link under different numbers of feedback bits are shown in figure 5. Apparently, the capacity increases with the large number of feedback bits.

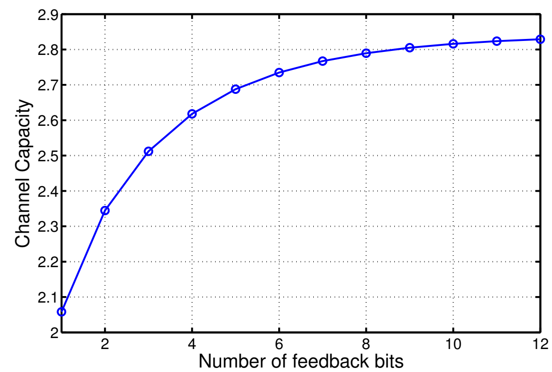

Fig. 5. Capacity of MIMO radio link under different numbers of feedback bits.

IV. Tradeoff Strategy

In section III, quantization impact on SI and CSI have been analyzed. Since the feedback is limited, we should allocate the limited bits to SI and CSI.

With the assumption that the number of total feedback bits $B=B_S+B_C$ is constant, objective function $\mathcal{R}$ is defined as follows

$$max\quad \mathcal{R}=(1-P_F(B_S))C(B_C) \tag{19}$$

subject to

$$\begin{aligned} B_S+B_C &= B\\ P_D(B_S,\lambda') &> P_{protect}\end{aligned}$$

where $P_{protect}$ is the minimum probability of detection the cognitive network should guarantee to protect the primary network from being interfered. P_F is corresponding probability of false alarm.

The objective function combines the sensing ability and channel capacity by defining a *valid capacity* which is only effective when the primary user is absent and the sensing result is correct. With the help of the objective function, we could figure out the optimal bit allocation strategy to maximize the valid capacity. Because the bits are allocating discretely, an exhaustion method could be used for calculating the value of the objective function in every bit allocation cases with linear complexity. The simulation results are shown in the section V.

V. Simulation Results

In this section, simulation results are given to demonstrate the performance of the proposed tradeoff strategy.

Figure.4 shows the valid capacity curve with different B_C, the number of total bits B = 6, and the average power at Tx and Rx are γ_t=γ_r=5dB, the lower bound of P_D is $P_{protect}$ =

0.9, and the percentage of the received energy below E_{max} is set to $(1 - 10^{-5})$

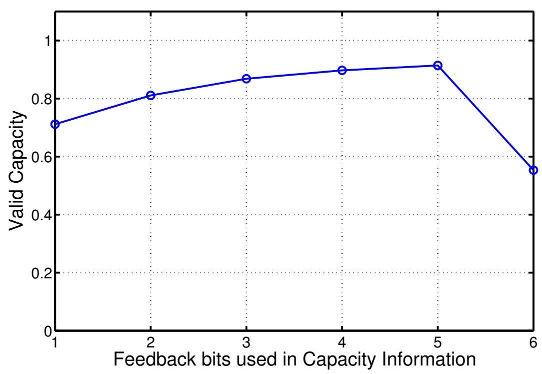

Fig. 6. Valid capacity under different bit allocations.

We can see from the figure that the valid capacity obtains the largest value when the number of bits used in SI is 1. From the figure 2 and the figure 5 in section III, it is obvious that the 1 bit feedback scheme in SI could reach the performance of the perfect feedback scheme and the bits used in CSI could obtain more benefits in valid capacity under this SNR.

From Figure 7, we can see that fewer bits should be allocated to CSI when SNR gets larger form 8dB to 16dB. The number of bits used in CSI is 2 when SNR = 8dB,10dB,12dB and 1 when SNR = 14dB, 16dB. Figure 3 in section III shows the upper bound of sensing benefits from cooperation, the upper bound increases when SNR changes from 8dB to 16dB. In that situation, allocating more bits in SI will obtain more benefits.

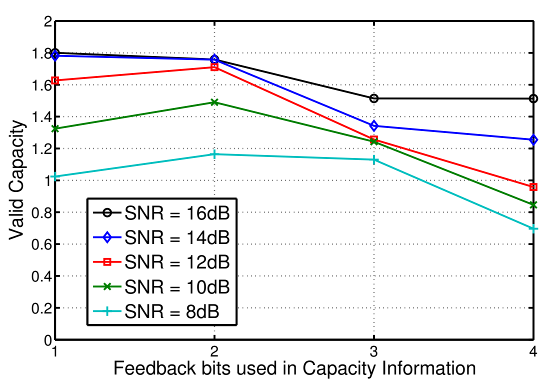

Fig. 7. Valid capacity versus Bit used in Capacity Information in different SNR .

A simulation result is given in figure 8, we set SNR = 10dB and the result of original scheme without cooperative sensing is given for comparing. Both schemes use the same amount of feedback bit which is 4. The proposed scheme uses a few bits for SI instead of using all bits for CSI. Figure 8 shows that the proposed cooperative sensing scheme has a better performance than the original scheme. Throughout the cooperative sensing, the proposed scheme has a better sensing ability.

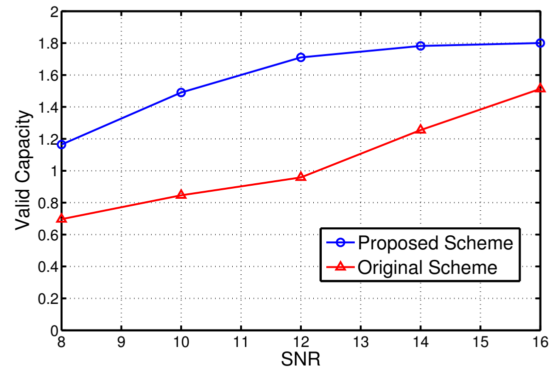

Fig. 8. Simulation results of valid capacity versus SNR.

VI. Conclusion

In this paper, we considered a cooperative sensing scheme using feedback channel in cognitive MIMO networks. Because the feedback channel is limited, the information should be quantized. The quantization impact on both cooperative sensing and capacity are analyzed. Then we proposed bits allocation strategy which spends several bits on sensing information to avoid the primary user from being interfered. Furthermore, a tradeoff criterion is proposed to balance the performance of the cognitive radio link as well as the interference towards the primary networks. The simulation results shows that the best allocation strategy changes with different SNRs. Finally, we examine the performance of the proposed scheme compared with original scheme.

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