

# Cooperative Spectrum Sensing with Ternary Local Decisions

Dongliang Duan and Liuqing Yang

**Abstract**—By collecting diversity among multiple sensing users, cooperative spectrum sensing can overcome the channel fading effect. Usually, only the local binary decisions are available for sensing cooperation due to the limited channel bandwidth. However, in our previous work [3], we have shown that this strategy will either compromise diversity or signal-to-noise ratio (SNR) gain. In this paper, we will study cooperative sensing with ternary local decisions. Compared with the binary cooperative sensing, this strategy can reclaim diversity and recover the SNR loss by appropriate threshold selection.

**Index Terms**—Spectrum sensing, diversity, ternary decisions.

## I. INTRODUCTION

OPPORTUNISTIC spectrum access schemes, a. k. a. cognitive radio systems, are proposed to solve the problem of spectrum scarcity via more efficient spectrum utilization [10] in lieu of today's fixed spectrum allocation strategy. There are various issues in realizing the cognitive radio system [4]. Among them, detecting the available unused spectrum resources, a. k. a. spectrum sensing, is the first step.

Extensive research has already been conducted to improve the spectrum sensing performance (see e.g. [1], [5], [7], [12], [13]). Among these, cooperative sensing is widely adopted as an efficient strategy to combat fading. In our previous work [3], the gain of cooperation is quantified in terms of the *cooperative diversities* for missed detection, false alarm and average error probabilities. Using diversity as the performance metric, we optimally designed the sensing threshold strategies for cooperative sensing with both soft information fusion (SCoS) and binary information fusion (BCoS). We found that while SCoS can achieve the maximum diversity, BCoS either loses half of the diversity or achieves the full diversity at the price of some signal-to-noise ratio (SNR) loss.

While the performance of SCoS is desirable, it is impractical since it requires infinite bandwidth for the communications between the sensing users and the fusion center. Intuitively, the performance gap between SCoS and BCoS results from the loss of information with the single-bit local decisions in BCoS. It should be possible to improve the performance by allowing the sensing users to provide more information. In this paper, we investigate a cooperative sensing scheme with local ternary decisions. While developing the optimum strategies is complicated and mathematically intractable, our focus is to

show that with local ternary decisions, it is possible to gain in terms of both diversity and SNR. This is in sharp contrary with the inevitable diversity-SNR tradeoff when binary local decisions are used.

Compared with existing work on cooperative spectrum sensing with multi-threshold local decisions such as [2], [6], [9], [8] and [11], our algorithm provides simple and closed-form expressions for both the local thresholds and fusion rule based on the metric of cooperative diversity. Moreover, we also obtain an explicit analytical expression for the performance gain, which has only been illustrated by simulations in the literature.

The problem formulation, together with the preliminaries of binary (BD) and ternary (TD) local decisions will be introduced in Section II. Then, we will determine the detection fusion rules for TD by first finding the relationship between BD and TD in Section III and then selecting the detection regions for TD in Section IV with simulation results given in Section V. Finally, concluding remarks will be presented in Section VI.

*Notation:*  $x \sim \mathcal{CN}(\mu, \sigma^2)$  denotes a complex Gaussian random variable  $x$  with mean  $\mu$  and variance  $\sigma^2$ .  $g(\gamma) \sim f(\gamma)$  means  $\lim_{\gamma \rightarrow +\infty} \frac{g(\gamma)}{f(\gamma)} = c$  where  $c > 0$  is a constant.  $g(\gamma) \approx f(\gamma)$  means  $\lim_{\gamma \rightarrow +\infty} \frac{g(\gamma)}{f(\gamma)} = 1$ .

## II. SYSTEM MODEL

### A. Signal Model and Performance Metrics

In the spectrum sensing process, the sensing users observe signals under the following two hypotheses:

$$\begin{aligned} H_0 &: \text{absence of primary user,} \\ H_1 &: \text{presence of primary user.} \end{aligned}$$

We assume that the channels between the primary and the sensing users are Rayleigh fading with additive white Gaussian noise (AWGN). Then after normalization, the signal at each sensing users becomes (see e.g. [3], [5]):

$$\begin{aligned} r_i | H_0 &= n_i \sim \mathcal{CN}(0, 1), \\ r_i | H_1 &= h_i x + n_i \sim \mathcal{CN}(0, \gamma + 1), \end{aligned} \quad (1)$$

where  $\gamma$  is the average SNR at the sensing users. With geographically distributed sensing users, it is reasonable to assume that they experience independent fading channels. With this assumption, the received signals for different sensing users  $r_i$ s are conditionally independent identically distributed (i.i.d.) under each hypothesis. Under this model, the Neyman-Pearson (NP) detector at each secondary user is the energy detector with  $\|r_i\|^2 \underset{H_0}{\overset{H_1}{\geq}} \theta_l$ , where  $\theta_l$  is the local decision threshold.

In our previous work [3], it has already been shown that the a priori probabilities of the hypotheses do not affect

Manuscript received April 9, 2012. The associate editor coordinating the review of this letter and approving it for publication was K. K. Wong.

D. Duan is with the Department of Electrical and Computer Engineering, University of Wyoming, 1000 E. University Ave., Laramie, WY 82071, USA (e-mail: duandongliang@gmail.com).

L. Yang (corresponding author) is with the Department of Electrical and Computer Engineering, Colorado State University, 1373 Campus Delivery, Fort Collins, CO 80523, USA (e-mail: lqyang@engr.colostate.edu).

This work is in part supported by the Office of Naval Research under grant #N00014-11-1-0667.

Part of the results in this paper has been presented at the IEEE International Conference on Acoustic, Speech and Signal Processing (ICASSP), Kyoto, Japan, March 2012.

Digital Object Identifier 10.1109/LCOMM.2012.072012.120764

the diversity gains. Therefore, without loss of generality, we assume that  $P(H_0 = 0) = P(H_1 = 1) = \frac{1}{2}$  in this paper.

For the detection problem introduced in Eq. (1), there are three performance measures, namely false alarm ( $P_f$ ), missed detection ( $P_{md}$ ) and average error ( $P_e$ ) probabilities. As in [3], we will use the diversity defined as  $d_* = -\lim_{\gamma \rightarrow +\infty} \frac{\log P_*}{\log \gamma}$  for each of them.

By definition, diversity only captures the performance at high SNR. Hence, in our analyses, we will aim at achieving better low-SNR performance while maintaining the same diversity gain.

### B. Binary Local Decision (BD) and BCoS- $k_0$

For BCoS introduced in [3], the secondary users make local binary decisions  $D_i \in \{0, 1\}$  and a fusion center will collect all decisions and make a global decision. The local decisions are:

$$D_i = \begin{cases} 0 & \text{if } 0 \leq \|r_i\|^2 < \theta_{l,B} \\ 1 & \text{if } \|r_i\|^2 > \theta_{l,B} \end{cases} \quad (2)$$

If the local decision threshold is  $\theta_{l,B} = k_0 \theta^o$ , where  $\theta^o = (1 + \frac{1}{\gamma}) \log(1 + \gamma)$  is the local optimum threshold by minimizing the local average error probability [3]. Then, as  $\gamma \rightarrow +\infty$ ,  $P_{f,l} = e^{-\theta_{l,B}} \approx \gamma^{-k_0}$  and  $P_{md,l} = e^{\frac{\theta_{l,B}}{\gamma+1}} \approx k_0 \gamma^{-1}$ . With the NP detector  $\sum_{i=1}^N D_i \stackrel{\geq H_0}{\geq} \theta_{f,B}$ , the diversities are  $d_{f,B} = k_0 \theta_{f,B}$  and  $d_{md,B} = N - \theta_{f,B} - 1$ , where  $N$  is the total number of secondary users. To jointly optimize both diversities, the fusion threshold can be selected as<sup>1</sup>:  $\arg \max_{\theta_{f,B}} (\min(k_0 \theta_{f,B}, N - \theta_{f,B} - 1)) = \frac{N+1}{k_0+1}$ . The optimized diversities can be determined accordingly as  $d_e = d_f = d_{md} = \frac{k_0}{k_0+1} (N+1)$ .

This indicates that with larger  $k_0$ , BCoS- $k_0$  can achieve higher diversities by setting larger local threshold. However, in this case, the local decisions have missed detection probabilities  $P_{md,B} \approx k_0 \gamma^{-1}$  with  $-10 \log_{10} k_0$  SNR loss and smaller false alarm probabilities  $P_{f,B} \approx \gamma^{-k_0}$ . The larger missed detection probability  $P_{md}$  will dominate the overall average error probabilities performance  $P_e$ . Furthermore, instead of the diversity gain, the SNR losses for the missed detection probabilities will dominate the overall average error probability  $P_e$  at low-to-medium SNR as shown in [3, Fig. 6].

### C. Ternary Local Decision (TD)

The local decisions for TD are:

$$D_i = \begin{cases} 0 & \text{if } 0 \leq \|r_i\|^2 < \theta_{l,1} \\ \spadesuit & \text{if } \theta_{l,1} \leq \|r_i\|^2 \leq \theta_{l,2} \\ 1 & \text{if } \|r_i\|^2 > \theta_{l,2} \end{cases} \quad (3)$$

where  $\theta_{l,2} > \theta_{l,1}$  are two local decision thresholds and  $\spadesuit$  means ‘‘not sure’’. Then, the ‘‘0’’ or ‘‘1’’ decisions<sup>2</sup> are sent to the fusion center for the global decision  $D \in \{0, 1\}$ .

<sup>1</sup>It should be noticed that at the fusion center,  $\sum D_i$ 's can only take integer values. However, to simplify the notation, the integer restrictions are neglected without affecting the analysis.

<sup>2</sup>Note that the sensor will remain silent when the local decision is  $\spadesuit$ .

Under this local decisions, the conditional probabilities under each hypothesis are:

$$\begin{aligned} P(D_i = 0|H_0) &= \alpha_1 = 1 - e^{-\theta_{l,1}}, \\ P(D_i = \spadesuit|H_0) &= \alpha_2 = e^{-\theta_{l,1}} - e^{-\theta_{l,2}}, \\ P(D_i = 1|H_0) &= \alpha_3 = e^{-\theta_{l,2}}, \\ P(D_i = 0|H_1) &= \beta_1 = 1 - e^{-\frac{\theta_{l,1}}{\gamma+1}}, \\ P(D_i = \spadesuit|H_1) &= \beta_2 = e^{-\frac{\theta_{l,1}}{\gamma+1}} - e^{-\frac{\theta_{l,2}}{\gamma+1}}, \\ P(D_i = 1|H_1) &= \beta_3 = e^{-\frac{\theta_{l,2}}{\gamma+1}}. \end{aligned} \quad (4)$$

At the fusion center,  $D_i$ s follow the trinomial distribution as:

$$\begin{aligned} P(D_1, D_2, \dots, D_N|H_0) &= \alpha_1^{n_0} \alpha_2^{N-n_0-n_1} \alpha_3^{n_1}, \\ P(D_1, D_2, \dots, D_N|H_1) &= \beta_1^{n_0} \beta_2^{N-n_0-n_1} \beta_3^{n_1}, \end{aligned} \quad (5)$$

where  $n_0 = \{\text{the number of } D_i = 0\}$ ,  $n_1 = \{\text{the number of } D_i = 1\}$  and  $N$  is the total number of cooperating local detectors. Accordingly, the sufficient statistics is  $(n_0, n_1)$ . Denoting  $\mathcal{R}_1$  as the set of  $(n_0, n_1)$  to make global decision  $D = 1$  and  $\mathcal{R}_0$  vice versa, we have:

$$\begin{aligned} P_f &= \sum_{(n_0, n_1) \in \mathcal{R}_1} P(n_0, n_1|H_0), \\ P_{md} &= \sum_{(n_0, n_1) \in \mathcal{R}_0} P(n_0, n_1|H_1). \end{aligned} \quad (6)$$

Based on Eqs. (4), (5) and (6), the optimum fusion rule can be obtained by jointly optimizing  $P_e = \frac{1}{2}(P_f + P_{md})$  over  $\theta_{l,1}$ ,  $\theta_{l,2}$  and  $\mathcal{R}_1$ . However, not only that this is mathematically intractable, the solution also does not provide any clear insights on the diversity-SNR tradeoff. As an alternative, we will first find the relationship between fusions with TD and BD and then develop the fusion rule for cooperative sensing with ternary local decisions (TCoS).

### III. THE LINK BETWEEN FUSIONS WITH BD AND TD

It is worth noting that at the fusion center, BD has a one-dimensional sufficient statistics set with  $n_0 + n_1 = N$  while TD has a two-dimensional set with  $n_0 + n_1 \leq N$ . We find that when the fusion center with TD makes a global decision based on only one of  $n_0$  and  $n_1$ , it is equivalent to the fusion with BD as the following:

**Theorem 1** For cooperative sensing based on local ternary decisions with thresholds  $\theta_{l,1}$  and  $\theta_{l,2}$ :

- 1) If  $\mathcal{R}_1 = \{(n_0, n_1) : n_1 \geq \theta_t\}$ , this TD fusion is equivalent to BD fusion with local threshold  $\theta_{l,B} = \theta_{l,2}$  and fusion threshold  $\theta_{f,B} = \theta_t$ ;
- 2) If  $\mathcal{R}_0 = \{(n_0, n_1) : n_0 \geq N - \theta_t + 1\}$ , this TD fusion is equivalent to BD fusion with local threshold  $\theta_{l,B} = \theta_{l,1}$  and fusion threshold  $\theta_{f,B} = \theta_t$ ;

*Proof:* If  $\mathcal{R}_1 = \{(n_0, n_1) : n_1 \geq \eta_t\}$ , then:

$$\begin{aligned} P_{f,t} &= \sum_{n_1=\eta_t}^N \sum_{n_0=0}^{N-n_1} \frac{N!}{n_0!(N-n_0-n_1)!n_1!} \alpha_1^{n_0} \alpha_2^{N-n_0-n_1} \alpha_3^{n_1} \\ &= \sum_{n_1=\eta_t}^N \frac{N}{n_1!(N-n_1)!} (1 - \alpha_3)^{N-n_1} \alpha_3^{n_1}, \end{aligned}$$

and

$$P_{md,t} = \sum_{n_1=0}^{\eta_t-1} \sum_{n_0=0}^{N-n_1} \frac{N!}{n_0!(N-n_0-n_1)!n_1!} \beta_1^{n_0} \beta_2^{N-n_0-n_1} \beta_3^{n_1} \\ = \sum_{n_1=0}^{\eta_t-1} \frac{N}{n_1!(N-n_1)!} (1-\beta_3)^{N-n_1} \beta_3^{n_1}.$$

This is equivalent to BT with  $\eta_{l,B} = \eta_{l,2}$  and  $\eta_{f,B} = \eta_t$ .

If  $\mathcal{R}_0 = \{(n_0, n_1) : n_0 \geq N+1-\eta_t\}$ , then:

$$P_{f,t} = \sum_{n_0=0}^{N-\eta_t+1} \sum_{n_1=0}^{N-n_0} \frac{N!}{n_0!(N-n_0-n_1)!n_1!} \alpha_1^{n_0} \alpha_2^{N-n_0-n_1} \alpha_3^{n_1} \\ = \sum_{n_0=0}^{N-\eta_t+1} \frac{N}{n_0!(N-n_0)!} \alpha_1^{n_0} (1-\alpha_1)^{N-n_0},$$

and

$$P_{md,t} = \sum_{n_0=N-\eta_t+1}^N \sum_{n_1=0}^{N-n_0} \frac{N!}{n_0!(N-n_0-n_1)!n_1!} \beta_1^{n_0} \beta_2^{N-n_0-n_1} \beta_3^{n_1} \\ = \sum_{n_0=N-\eta_t+1}^N \frac{N}{n_0!(N-n_0)!} \beta_1^{n_0} (1-\beta_1)^{N-n_0}.$$

This is equivalent to BT with  $\eta_{l,B} = \eta_{l,1}$  and  $\eta_{f,B} = \eta_t$ . ■

#### IV. TCoS FUSION RULE

With the relationship between BD and TD established in Theorem 1, we will next develop the fusion rule for TCoS. In particular, with local sensing thresholds  $\theta_{l,1} = k_1\theta^o$  and  $\theta_{l,2} = k_2\theta^o$  and  $k_1 < k_2$ , the corresponding sensing strategy is termed as TCoS- $k_1$ - $k_2$ .

Recall that from Section II-B, BCoS- $k_1$  has a smaller diversity order. On the other hand, BCoS- $k_2$  achieves larger diversity but suffers from the SNR loss with the missed detection probability. Therefore, here we try to improve BCoS- $k_2$  missed detection performance by moving part of the decision region  $\mathcal{R}_0$  to  $\mathcal{R}_1$  while maintaining its larger false alarm and hence the overall diversity.

With TCoS- $k_1$ - $k_2$ , the probabilities for local decisions are:  $\alpha_1 \approx 1-\gamma^{-k_1}$ ,  $\alpha_2 \approx \gamma^{-k_1}$ ,  $\alpha_3 \approx \gamma^{-k_2}$  and  $\beta_1 \approx k_1\gamma^{-1}$ ,  $\beta_2 \approx (k_2-k_1)\gamma^{-1}$ ,  $\beta_3 \approx 1-k_2\gamma^{-1}$ . Accordingly,

$$P(n_0, n_1|H_0) \approx \alpha_2^{N-n_0-n_1} \alpha_3^{n_1} \sim \gamma^{-(k_1N-k_1n_0+(k_2-k_1)n_1)} \quad (7) \\ P(n_0, n_1|H_1) \approx \beta_1^{n_0} \beta_2^{N-n_0-n_1} \sim \gamma^{-(N-k_1)} \quad (8)$$

The false alarm probability can be then calculated as:

$$P_f = \sum_{(n_0, n_1) \in \mathcal{R}_1} P(n_0, n_1|H_0) \\ \sim \sum_{(n_0, n_1) \in \mathcal{R}_1} \gamma^{-(k_1N-k_1n_0+(k_2-k_1)n_1)}. \quad (9)$$

By Theorem 1, the decision region corresponding to BCoS- $k_2$  is  $\mathcal{R}_1 = \{(n_0, n_1) : n_1 \geq \frac{N+1}{k_2+1}\}$ ,  $\mathcal{R}_0 = \{(n_0, n_1) : n_1 < \frac{N+1}{k_2+1}\}$  and  $d_{f,BCoS-k_2} = \frac{k_2}{k_2+1}(N+1)$ . In order to reduce the missed detection probability which dominates the average error performance, we want to increase the decision region of  $\mathcal{R}_1$ , or equivalently decrease  $\mathcal{R}_0$ . At the same time, however, the false alarm diversity should be preserved. From Eq. (7), if  $k_1N-k_1n_0+(k_2-k_1)n_1 \geq \frac{k_2}{k_2+1}(N+1)$ , or equivalently  $n_0 \leq$

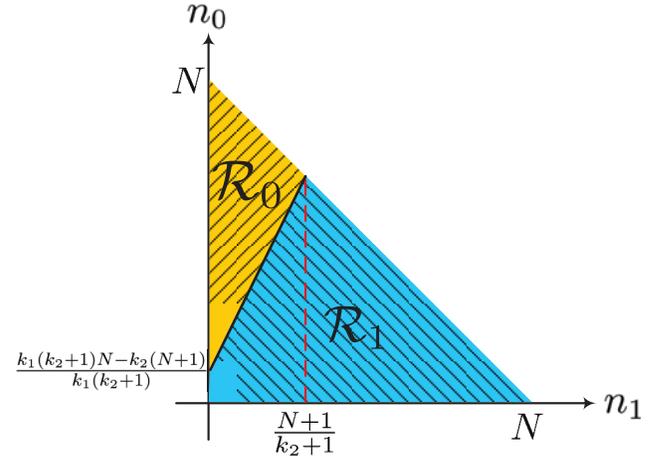


Fig. 1. The decision region for TCoS- $k_1$ - $k_2$  with the points at the boundary belonging to  $\mathcal{R}_1$ .

$(k_2-k_1)n_1 + \frac{k_1(k_2+1)N-k_2(N+1)}{k_2+1}$ ,  $P(n_0, n_1|H_0)$  will have a larger exponent of  $\gamma^{-1}$  than  $d_{f,BCoS-k_2}$ . Therefore, all points in  $\mathcal{R}_0$  satisfying  $n_0 \leq (k_2-k_1)n_1 + \frac{k_1(k_2+1)N-k_2(N+1)}{k_2+1}$  can be moved into  $\mathcal{R}_1$  without affecting the false alarm diversity according to (9). As a result, the boundary between  $\mathcal{R}_1$  and  $\mathcal{R}_0$  of the resultant fusion rule is the line  $n_0 = (\frac{k_2}{k_1}-1)n_1 + \frac{k_1(k_2+1)N-k_2(N+1)}{k_1(k_2+1)}$ , which starts from  $(n_0, n_1) = (\frac{k_1(k_2+1)N-k_2(N+1)}{k_1(k_2+1)}, 0)$  and ends at  $(n_0, n_1) = (\frac{k_2N-1}{k_2+1}, \frac{N+1}{k_2+1})$  where  $\frac{k_2N-1}{k_2+1} + \frac{N+1}{k_2+1} = N$ .

The decision region for TCoS- $k_1$ - $k_2$  is illustrated in Fig. 1. The bold line is the boundary between  $\mathcal{R}_0$  and  $\mathcal{R}_1$  for TCoS- $k_1$ - $k_2$  while the dashed line is the boundary corresponding to BCoS- $k_2$ .

Compared with BCoS- $k_2$ , TCoS- $k_1$ - $k_2$  will provide the same overall diversities with  $d_e = d_{md} = d_f = \frac{N+1}{k_2+1}$ . Denoting  $\Delta\mathcal{R} = \{(n_0, n_1) : 0 \leq n_1 < \frac{N+1}{k_2+1}, 0 \leq n_0 \leq (k_2-k_1)n_1 + \frac{k_1(k_2+1)N-k_2(N+1)}{k_2+1}\}$ , the difference between the missed detection probabilities of TCoS- $k_1$ - $k_2$  and BCoS- $k_2$  is

$$\Delta P_{md} = P_{md, TCoS-k_1-k_2} - P_{md, BCoS-k_2} = - \sum_{\Delta\mathcal{R}} \beta_1^{n_0} \beta_2^{N-n_0-n_1} \beta_3^{n_1}, \quad (10)$$

and the difference between the false alarm probabilities of TCoS- $k_1$ - $k_2$  and BCoS- $k_2$  is

$$\Delta P_f = P_{f, TCoS-k_1-k_2} - P_{f, BCoS-k_2} = \sum_{\Delta\mathcal{R}} \alpha_1^{n_0} \alpha_2^{N-n_0-n_1} \alpha_3^{n_1}. \quad (11)$$

It should be noticed that  $\Delta P_e = P_{e, TCoS-k_1-k_2} - P_{e, BCoS-k_2} = \frac{1}{2}(\Delta P_{md} + \Delta P_f) < 0$ . Therefore, we obtain overall performance gain over BCoS- $k_2$ . This once again confirms that TCoS not only keeps the diversity gain that captures high SNR performance but also improves the SNR gain that characterizes the low-to-medium.

#### V. SIMULATIONS

Although it is possible to optimize  $k_1$  for any given  $k_2$  to obtain the maximum performance gain of TCoS by the analytical expressions given in Section IV, the complexity is high. Therefore, we opt to verify and demonstrate the

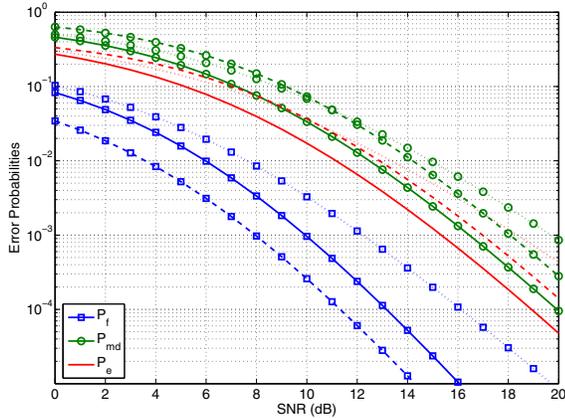


Fig. 2. TCoS-1-2 (solid) vs. BCoS-1 (dotted) and BCoS-2 (dashed) with  $N = 5$ .

performance gain of TCoS over BCoS using some simple  $k_1$  and  $k_2$  values.

To illustrate the performance gain of TCoS- $k_1$ - $k_2$  over both BCoS- $k_1$  and BCoS- $k_2$ , we simulate TCoS-1-2 with 5 cooperating users and compare its performance with BCoS-1 and BCoS-2 in Fig. 2. We see that BCoS-2 exhibit a higher diversity than BCoS-1, but a worse performance at low SNR. Our proposed TCoS-1-2 not only retains the higher diversity of BCoS-2 but also has better performance at low SNR.

In Fig. 3, the performance of our proposed TCoS-1-2 is compared with the optimal TCoS with exhaustive search. It can be seen that our TCoS-1-2 only sacrifices a little performance ( $\approx 1.5$  dB) in exchange for the low-complexity closed-form local and global decision rules.

In addition, we know that BCoS- $N$  achieves the maximum diversity but suffers from considerable SNR loss. Here, we compare the performance of TCoS-2.5-5 and BCoS-5 in Fig. 4. It can be observed that TCoS-2.5-5 also achieves the same full diversity ( $d_e = 5$ ), but has about 2dB SNR gain. Together with Fig. 2, it is confirmed that the overall SNR gain is obtained without losing any false alarm diversity.

## VI. CONCLUDING REMARKS

In this paper, we proposed cooperative sensing with ternary local decisions (TCoS) to improve upon binary hard decisions (BCoS) by gaining SNR while maintaining the same diversity. The link between the fusion with BD and TD has been established and further used to determine the fusion rule for TCoS. The algorithm developed in this paper provides simple and closed-form expressions for both the local decision thresholds and the fusion rule. The performance gain was also derived analytically. Furthermore, simulations confirmed that, as the middle ground between BCoS and SCoS, TCoS provides a practical yet effective solution for the inevitable diversity-SNR tradeoff encountered by BCoS.

## REFERENCES

- [1] D. Cabric, A. Tkachenko, and R. W. Brodersen, "Experimental study of spectrum sensing based on energy detection and network cooperation," in *Proc. 2006 ACM Int. Workshop on Technology and Policy for Accessing Spectrum*.
- [2] S. Chaudhari, J. Lunden, V. Koivunen, and H. V. Poor, "Cooperative sensing with imperfect reporting channels: hard decisions or soft decisions?" *IEEE Trans. Signal Process.*, vol. 60, no. 1, pp. 18–28, Jan. 2010.

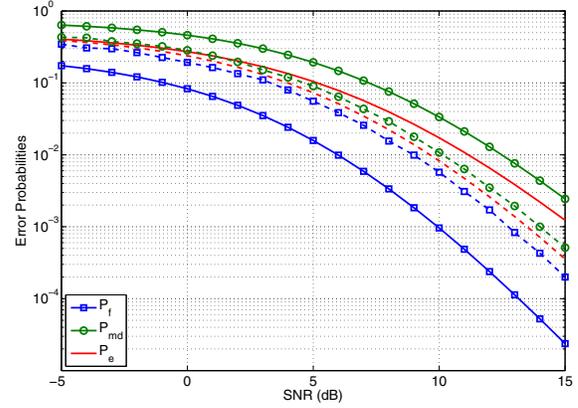


Fig. 3. TCoS-1-2 (solid) vs. optimal TCoS by exhaustive search (dashed) with  $N = 5$ .

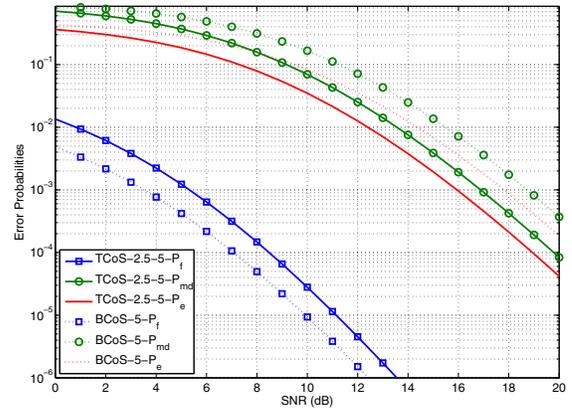


Fig. 4. TCoS-2.5-5 vs. BCoS-5 with  $N = 5$ .

- [3] D. Duan, L. Yang, and J. C. Principe, "Cooperative diversity of spectrum sensing for cognitive radio networks," *IEEE Trans. Signal Process.*, vol. 58, no. 6, pp. 3218–3227, June 2010.
- [4] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.
- [5] S. Hong, M. H. Vu, and V. Tarokh, "Cognitive sensing based on side information," in *2008 IEEE Sarnoff Symposium*.
- [6] P. Kaewprapha, J. Li, and Y. Yu, "Cooperative spectrum sensing with tri-state probabilistic inference," in *Proc. 2010 Military Communications Conference*, pp. 318–323.
- [7] S.-J. Kim, E. Dall'Anese, and G. B. Giannakis, "Cooperative spectrum sensing for cognitive radios using kriged Kalman filters," *IEEE J. Sel. Topics Signal Process.*, vol. 5, no. 1, pp. 24–36, Feb. 2011.
- [8] J. Ma, G. Zhao, and Y. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 7, no. 11, pp. 4502–4507, Nov. 2008.
- [9] S. M. Mishra, R. Tandra, and A. Sahai, "The case for multiband sensing," in *Proc. 2007 Allerton Conference on Communication, Control, and Computing*. Available: <http://php/pubs/pubs.php/114.html>
- [10] J. Mitola III and G. Q. Maguire Jr., "Cognitive radio: making software radios more personal," *IEEE Personal Commun.*, vol. 6, no. 4, pp. 13–18, Aug. 1999.
- [11] M. Mustonen, M. Matinmikko, and A. Mämmälä, "Cooperative spectrum sensing using quantized soft decision combining," in *Proc. 2009 International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, pp. 1–5.
- [12] Z. Quan, S. Cui, and A. H. Sayed, "Optimal linear cooperation for spectrum sensing in cognitive radio networks," *IEEE J. Sel. Topics Signal Process.*, vol. 2, no. 1, pp. 28–40, Feb. 2008.
- [13] J. Unnikrishnan and V. V. Veeravalli, "Cooperative sensing for primary detection in cognitive radio," *IEEE J. Sel. Topics Signal Process.*, vol. 2, no. 1, pp. 18–27, Feb. 2008.