PARTIALLY COHERENT DISTRIBUTED DETECTION UNDER TOTAL POWER CONSTRAINT

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ABSTRACT

In this paper, we consider the problem of power constrained partially coherent distributed detection over fading multi-access channel. The deflection coefficient maximization (DCM) is used to optimize the performance of detectors. Two cases of the channel gain information are considered separately at the fusion center, one case with perfect channel gain (the corresponding method is referred to as PC-DCM, with PC being the abbreviation for "partially coherent"), the other case with statistical information of channel gain (the corresponding method is referred to as PC-DCM-CS, with CS being the abbreviation for "channel statistics"). We derive the closed-form solutions to the considered problems. Monte-Carlo simulations are carried out to verify the performance of the proposed methods. Simulation results show that the proposed new methods could significantly improve the detection performance of the fusion system at low signal-to-noise ratio (SNR).

Index Terms— Distributed detection, partially coherent, deflection coefficient maximization, power constraint, multi-access channel

1. INTRODUCTION

With the significant development in the fields of intelligent sensors, wireless communications and networking, distributed detection using multiple sensors has become a fast-growing research area [1]-[3]. Compared to a centralized scheme where all raw observation data is communicated to the fusion center, distributed detection scheme could dramatically reduce the communication bandwidth and thus is very competitive candidate to be implemented in wireless sensor networks [4]-[7]. However, to implement distributed detection in networking, we meet some new challenges. One challenge is the stringent power constraint. Normally, local sensors are powered by small batteries and it is difficult or not economic to replace those batteries when they run out. Therefore, power management is considered to be an important issue in distributed detection.

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Numerous researchers have focused on the usual parallel topology which assumes that each sensor transmits through a parallel access channel (PAC). For this scheme, a dedicated channel will be established for each sensor that wishes to communicate with the fusion center [4], [5]. Recently, distributed detection over multiple access channels (MAC) has received much attention, it has been verified that in some cases the MAC scheme could offer high efficiency in bandwidth usage and achieve a significant improvement in performance compared to the PAC scheme when a large number of sensors are deployed [8], [9], [13]. The problem of distributed detection under power constraints has been studied by many researchers [10]-[12]. Using the PAC, in [10], it was shown that the performance is asymptotically optimal for binary decentralized detection using identical sensor nodes under joint power constraint. Using the MAC, in [11], the optimal quantization function has been studied under the total power constraint which assumed the sensors are homogeneous. In [12], it was showed that under the total power constraint, MAC fusion results in exponential decay in error exponents with the number of sensors, while PAC fusion does not. However, most of the above authors assumed perfectly phase coherent reception at the fusion center. In practice, this assumption will be too strong. In this paper, we relax the assumption of perfectly coherent reception and study the problem of total power constrained partially coherent detection over fading Multi-access Channel.

2. SYSTEM MODEL

The model of the distributed detection system considered here is illustrated in Fig. 1, where the system consists of N sensors and a fusion center (FC). Here, H_0 denotes the null hypothesis (e.g., the target is absent), and H_1 denotes the alternative hypothesis (e.g., the target is present). The prior probabilities for both hypothesis (denoted by P_0 and P_1, respectively) are assumed known. Assume y_i be the observation obtained by the i-th sensor. Each sensor performs binary detection and generates a local decision based on its own measurement. We do not assume any determined distribution for observations but do assume the observations are all conditionally independent on any hypothesis. The same as literature [5], in this paper, we assume flat fading channels between local sensors and the FC. We adopt the ON-OFF keying (OOK) mode, i.e., $u_i = 1$ if the i-th sensor is in favor of H_1, and $u_i = 0$ otherwise. Here $i = 1, 2, \ldots, N$. We characterize the detection performance of the i-th sensor node by its false alarm probability P_{fi} and detection probability P_{di}, which are defined as $P_{fi} = p(u_i = 1|H_0)$ and $P_{di} = p(u_i = 1|H_1)$, respectively.

The local decisions are modulated firstly, and then transmitted over fading and noisy channels to the fusion center. The MAC scheme allows all the sensors to transmit simultaneously over the same channel [6], the fusion center observes a superposition of the signals sent by the local sensors, the

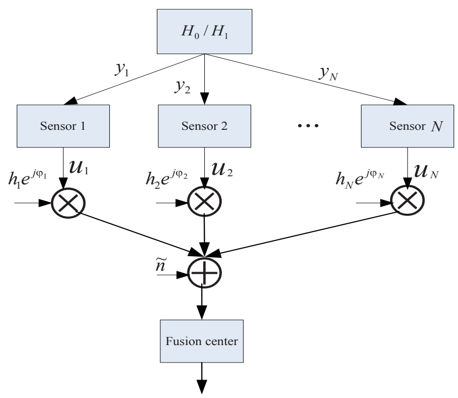

Fig. 1. System model.

signal S received by the fusion center can be expressed as

$$S = \sum_{i=1}^{N} \sqrt{g_i} u_i h_i e^{j\varphi_i} + \tilde{n}, \tag{1}$$

where $\sqrt{g_i}$ $(1 \leq i \leq N)$ is the nonnegative weight coefficient which will modulate the i-th transmitted waveform (usually, it is a baseband signal). h_i $(1 \leq i \leq N)$ denotes the fading channel gain between the i-th local sensor and the FC. $\varphi_i \in [-\pi, \pi]$ is the channel phase, and we assume that φ_i is uniform distribution. $\tilde{n}$ is zero mean complex Gaussian noise with variance $2\sigma^2$, that is $\tilde{n} \sim CN(0, 2\sigma^2)$. Usually, we assume phase coherent reception at the fusion center; this could be either accomplished through limited training for stationary channels, or, at a small cost of SNR degradation, by employing differential encoding for fast fading channels. However, we account for the fact that the phase synchronization is never perfect at the fusion center. Let $\hat{\varphi}_i$ be the estimation of the i-th channel phase, then we assume the corresponding sensor could use $\hat{\varphi}_i$ to correct the channel phase before transmission (i.e., the i-th transmitted waveform will be multiplied by $e^{-j\hat{\varphi}_i}$). Thus the information received by the fusion center can be described as

$$\hat{S} = \sum_{i=1}^{N} \sqrt{g_i} u_i h_i e^{j\tilde{\varphi}_i} + \tilde{n}, \tag{2}$$

here $\tilde{\varphi}_i = \varphi_i - \hat{\varphi}_i$ is the residual phase error after correction. In practice, the phase-locked loop is usually used to estimate the channel phase [14], [15]. The probability density function (PDF) of the phase error can be suitably modeled by the Tikhonov distribution [16], [17]. Therefore, we have the PDF of the channel phase error as follows

$$f_{\tilde{\varphi}}(x) = \frac{e^{\beta \cos(x)}}{2\pi I_0(\beta)}, \ -\pi < x < \pi, \tag{3}$$

where $I_n(x)$ is the modified Bessel function of the first kind of order n, and $\beta \geq 0$ is the shape parameter, we note that the larger the value of β is, the smaller of the channel phase error will be, i.e. while $\beta \to \infty$ corresponds to the perfect phase information. From (2), we observe that $\hat{S}$ is a complex variable, thus we use the real part function $R(\cdot)$ to get $R(\hat{S})$ (for convenience, let $Y = R(\hat{S})$) as follows

$$Y = R(\hat{S}) = \sum_{i=1}^{N} \sqrt{g_i} u_i h_i \cos(\tilde{\varphi}_i) + n. \tag{4}$$

Where n is zero mean Gaussian noise with variance σ^2, that is $n \sim N(0, \sigma^2)$. The global decision is made by involving a comparison of Y with a threshold [5].

3. DISTRIBUTED DETECTION VIA DEFLECTION COEFFICIENT MAXIMIZATION

The deflection coefficient could reflect the output-signal-to-noise-ratio and has been widely used in optimizing detectors [23]. The larger the deflection coefficient is, the better the performance of the system will be. It is worth noting that the use of deflection criterion leads to the optimum likelihood ratio (LR) receiver in many cases of practical applications [24]. We therefore are motivated to optimize the performance of fusion system via maximizing the deflection coefficient. The deflection coefficient is defined as

$$D(Y) = \frac{[\mathrm{E}(Y|H_1) - \mathrm{E}(Y|H_0)]^2}{\mathrm{Var}(Y|H_0)}, \tag{5}$$

where $\mathrm{E}(\cdot|H_j)$ and $\mathrm{Var}(\cdot|H_j)$ $(j = 0, 1)$ denote the expected value and variance under condition H_j, respectively.

4. DISTRIBUTED DETECTION UNDER TOTAL POWER CONSTRAINT

The total power constrained optimization problem can be formulated as

$$\begin{aligned} \max \quad & D(Y) \\ \text{s.t.} \quad & \sum_{i=1}^{N} \mathrm{E}\{|\sqrt{g_i} u_i e^{-j\hat{\varphi}_i}|^2\} \leq P, \\ & g_i \geq 0, \ 1 \leq i \leq N, \end{aligned} \tag{6}$$

here, P is the total power budget. Our aim is to derive the optimal values of g_i.

4.1. PC-DCM method

Assume h_i, u_i and $\tilde{\varphi}_i$ are independent, then, using (4), we have

$$\mathrm{E}(Y|H_j) = \sum_{i=1}^{N} \sqrt{g_i} h_i \mathrm{E}(u_i|H_j)\mathrm{E}(\cos(\tilde{\varphi}_i)), \tag{7}$$

$$\mathrm{E}(u_i|H_j) = \begin{cases} P_{di}, & \text{if } j = 1, \\ P_{fi}, & \text{if } j = 0, \end{cases} \tag{8}$$

from (3), we have

$$\mathrm{E}(\cos(\tilde{\varphi}_i)) = \int_{-\pi}^{\pi} cos(x) \frac{e^{\beta \cos(x)}}{2\pi I_0(\beta)} dx = \frac{I_1(\beta)}{I_0(\beta)}, \tag{9}$$

$$\mathrm{Var}(Y|H_0) = \sum_{i=1}^{N} g_i h_i^2 \mathrm{Var}(u_i \cos(\tilde{\varphi}_i)|H_0) + \sigma^2, \tag{10}$$

$$\mathrm{Var}(u_i \cos(\tilde{\varphi}_i)|H_0) = \frac{\frac{1}{\beta} I_1(\beta) + I_2(\beta)}{I_0(\beta)} P_{fi} - [\frac{I_1(\beta)}{I_0(\beta)}]^2 P_{fi}^2, \tag{11}$$

where the last equality in (9) and (11) follows by property of the Bessel function [25]. Thus, $D(Y)$ can be obtained using (7)$\sim$(11), the optimization problem (6) becomes

$$\begin{aligned} \max \quad & \frac{\left[\sum_{i=1}^{N} \sqrt{g_i} h_i \frac{I_1(\beta)}{I_0(\beta)} (P_{di} - P_{fi})\right]^2}{\sum_{i=1}^{N} g_i h_i^2 \{\frac{\frac{1}{\beta} I_1(\beta) + I_2(\beta)}{I_0(\beta)} P_{fi} - [\frac{I_1(\beta)}{I_0(\beta)}]^2 P_{fi}^2\} + \sigma^2} \\ \text{s.t.} \quad & \sum_{i=1}^{N} \mathrm{E}\{|\sqrt{g_i} u_i e^{-j\hat{\varphi}_i}|^2\} = \sum_{i=1}^{N} g_i (P_0 P_{fi} + P_1 P_{di}) \le P, \\ & g_i \ge 0, \ 1 \le i \le N. \end{aligned} \tag{12}$$

Denote the vector $\boldsymbol{a} = (a_1, a_2, \ldots, a_i, \ldots, a_N)^T$ with $a_i = \sqrt{P}(h_i/c_i)[I_1(\beta)/I_0(\beta)](P_{di} - P_{fi})$, the diagonal matrix $\boldsymbol{B} = \mathrm{diag}(b_1, b_2, \ldots, b_i, \ldots, b_N)$ with $b_i = P(h_i^2/c_i^2)\{[(1/\beta)I_1(\beta) + I_2(\beta)/I_0(\beta)]P_{fi} - [I_1(\beta)/I_0(\beta)]^2 P_{fi}^2\}$, and the vector $\boldsymbol{\omega} = (\omega_1, \omega_2, \ldots, \omega_i, \ldots, \omega_N)^T$ with $\omega_i = c_i\sqrt{g_i}/\sqrt{P}$, where $c_i = \sqrt{P_0 P_{fi} + P_1 P_{di}}$. With the above notations, problem (12) can be equivalently rewritten as

$$\begin{aligned} \max \quad & \frac{\boldsymbol{\omega}^T \boldsymbol{a}\boldsymbol{a}^T \boldsymbol{\omega}}{\boldsymbol{\omega}^T \boldsymbol{B} \boldsymbol{\omega} + \sigma^2} \\ \text{s.t.} \quad & \|\boldsymbol{\omega}\|_2^2 \le 1, \ \boldsymbol{\omega} \ge \boldsymbol{0}. \end{aligned} \tag{13}$$

We assume $\boldsymbol{\omega_o}$ is the optimal solution to (13), then we claim $\|\boldsymbol{\omega}_0\|_2^2 = 1$. The proof is as follows, suppose $\|\boldsymbol{\omega}_0\|_2^2 < 1$, let $\hat{\boldsymbol{\omega}}_\mathbf{0} = \boldsymbol{\omega_0}/\|\boldsymbol{\omega_0}\|$, then $\|\hat{\boldsymbol{\omega}}_\mathbf{0}\|_2^2 = 1$, we know

$$\frac{\hat{\boldsymbol{\omega}}_\mathbf{0}^T \boldsymbol{a}\boldsymbol{a}^T \hat{\boldsymbol{\omega}}_\mathbf{0}}{\hat{\boldsymbol{\omega}}_\mathbf{0}^T \boldsymbol{B} \hat{\boldsymbol{\omega}}_\mathbf{0} + \sigma^2} = \frac{\boldsymbol{\omega}_0^T \boldsymbol{a}\boldsymbol{a}^T \boldsymbol{\omega}_0}{\boldsymbol{\omega}_0^T \boldsymbol{B} \boldsymbol{\omega}_0 + \|\boldsymbol{\omega}_0\|_2^2 \sigma^2} > \frac{\boldsymbol{\omega}_0^T \boldsymbol{a}\boldsymbol{a}^T \boldsymbol{\omega}_0}{\boldsymbol{\omega}_0^T \boldsymbol{B} \boldsymbol{\omega}_0 + \sigma^2}, \tag{14}$$

which is a contradiction. Therefore (13) can be equivalently converted into

$$\begin{aligned} \max \quad & \frac{\boldsymbol{\omega}^T \boldsymbol{a}\boldsymbol{a}^T \boldsymbol{\omega}}{\boldsymbol{\omega}^T (\boldsymbol{B} + \sigma^2 \boldsymbol{I}) \boldsymbol{\omega}} \\ \text{s.t.} \quad & \|\boldsymbol{\omega}\|_2^2 = 1, \ \boldsymbol{\omega} \ge \boldsymbol{0}. \end{aligned} \tag{15}$$

Let $\boldsymbol{x} = \boldsymbol{A}\boldsymbol{\omega}$ with $\boldsymbol{A} = (\boldsymbol{B} + \sigma^2 \boldsymbol{I})^{\frac{1}{2}}$, we notice that A is a diagonal and also positive definite matrix, then $\boldsymbol{\omega} = \boldsymbol{A}^{-1}\boldsymbol{x} = (\boldsymbol{B} + \sigma^2 \boldsymbol{I})^{-\frac{1}{2}} \boldsymbol{x}$, (15) becomes

$$\begin{aligned} \max \quad & \frac{\boldsymbol{x}^T \boldsymbol{A}^{-1} \boldsymbol{a}\boldsymbol{a}^T \boldsymbol{A}^{-1} \boldsymbol{x}}{\boldsymbol{x}^T \boldsymbol{x}} \\ \text{s.t.} \quad & \|\boldsymbol{A^{-1}x}\|_2^2 = 1, \ \boldsymbol{x} \ge \boldsymbol{0}. \end{aligned} \tag{16}$$

(16) is an eigenvalue problem, since $\mathrm{Rank}(\boldsymbol{A}^{-1}\boldsymbol{a}\boldsymbol{a}^T\boldsymbol{A}^{-1}) = 1$, thus, the optimal solution to (16) is the eigenvector of the matrix $\boldsymbol{A}^{-1}\boldsymbol{a}\boldsymbol{a}^T\boldsymbol{A}^{-1}$ corresponding to the maximum eigenvalue. Therefore, the optimal solution to problem (12) is

$$g_i = \frac{P(\boldsymbol{\omega}_o)_i^2}{P_0 P_{fi} + P_1 P_{di}}, \tag{17}$$

where $(\boldsymbol{\omega}_o)_i$ denotes the i-th component of the vector $\boldsymbol{\omega}_o$, $\boldsymbol{\omega}_o = \boldsymbol{\omega}_a/\|\boldsymbol{\omega}_a\|$, $\boldsymbol{\omega}_a = (\boldsymbol{B} + \sigma^2 \boldsymbol{I})^{-1} \boldsymbol{a}$.

4.2. PC-DCM-CS method

In this case, only the statistical information of channel gain is known to the FC, thus, we have

$$\mathrm{E}(Y|H_j) = \sum_{i=1}^{N} \sqrt{g_i} \mathrm{E}(u_i|H_j) \mathrm{E}(h_i) \mathrm{E}(\cos(\tilde{\varphi}_i)), \tag{18}$$

$$\mathrm{Var}(Y|H_0) = \sum_{i=1}^{N} g_i \mathrm{Var}(u_i h_i \cos(\tilde{\varphi}_i)|H_0) + \sigma^2. \tag{19}$$

Notice that $\mathrm{Var}(u_i h_i \cos(\tilde{\varphi}_i)|H_0)$ is the variance of the product of three independent random variables, from [26], we have

$$\mathrm{Var}(u_i h_i \cos(\tilde{\varphi}_i)|H_0) = \prod_{k=1}^{3} (V_k + X_k^2) - \prod_{k=1}^{3} (X_k^2), \tag{20}$$

here V_k $(k = 1, 2, 3)$ is the conditional variance of u_i, h_i and $\cos(\tilde{\varphi}_i)$, X_k $(k = 1, 2, 3)$ is the conditional expectation of u_i, h_i and $\cos(\tilde{\varphi}_i)$ under H_0, respectively. We have $V_1 = P_{fi} - P_{fi}^2$, $V_2 = \mathrm{E}(h_i^2) - \mathrm{E}^2(h_i)$, $V_3 = [(1/\beta)I_1(\beta) + I_2(\beta)]/I_0(\beta) - [I_1(\beta)/I_0(\beta)]^2$, $X_1 = P_{fi}$, $X_2 = \mathrm{E}(h_i)$, $X_3 = I_1(\beta)/I_0(\beta)$, where we get V_3 using the property of the Bessel function [26]. Then

$$\begin{aligned} \mathrm{Var}(u_i h_i \cos(\tilde{\varphi}_i)|H_0) = {} & P_{fi} \mathrm{E}(h_i^2)[(1/\beta)I_1(\beta) + I_2(\beta)]/I_0(\beta) \\ & - P_{fi}^2 \mathrm{E}^2(h_i)[I_1(\beta)/I_0(\beta)]^2. \end{aligned} \tag{21}$$

Thus, the optimization problem (6) becomes

$$
\begin{aligned}
\max \quad & \frac{\left[\sum_{i=1}^{N} \sqrt{g_i}\mathrm{E}(h_i)\frac{I_1(\beta)}{I_0(\beta)}(P_{di}-P_{fi})\right]^2}{\sum_{i=1}^{N} g_i \mathrm{Var}(u_i h_i \cos(\tilde{\varphi}_i)|H_0)+\sigma^2} \\
\text{s.t.} \quad & \sum_{i=1}^{N} \mathrm{E}\{|\sqrt{g_i}u_i e^{-j\hat{\varphi}_i}|^2\} = \sum_{i=1}^{N} g_i(P_0 P_{fi} + P_1 P_{di}) \le P, \\
& g_i \ge 0,\ 1 \le i \le N. \qquad (22)
\end{aligned}
$$

Denote the vector $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \ldots, \gamma_i, \ldots, \gamma_N)^T$ with $\gamma_i = \sqrt{P}[\mathrm{E}(h_i)/c_i][I_1(\beta)/I_0(\beta)](P_{di} - P_{fi})$, the diagonal matrix $\boldsymbol{M} = \mathrm{diag}(m_1, m_2, \ldots, m_i, \ldots, m_N)$ with $m_i = P\mathrm{Var}(u_i h_i \cos(\tilde{\varphi}_i)|H_0)/c_i^2$. Following the similar derivation process outlined in 4.1, the optimal solution to problem (22) is

$$
g_i = \frac{P(\boldsymbol{\varpi_o})_i^2}{P_0 P_{fi} + P_1 P_{di}}, \qquad (23)
$$

where $(\boldsymbol{\varpi_o})_i$ denotes the i-th component of the vector $\boldsymbol{\varpi_o}$, $\boldsymbol{\varpi}_o = \boldsymbol{\varpi}_a/\|\boldsymbol{\varpi}_a\|$, $\boldsymbol{\varpi}_a = (\boldsymbol{M} + \sigma^2\boldsymbol{I})^{-1}\boldsymbol{\gamma}$.

5. NUMERICAL SIMULATION

In our simulation, we assume a Rayleigh fading channel, i.e., the pdf of h_i is $f(h_i) = 2h_i e^{-h_i^2}$, $h_i \ge 0$. $\mathrm{E}(h_i) = \sqrt{\pi}/2$, $\mathrm{E}(h_i^2) = 1$. We set $N = 8$, $\vec{P}_d = \{0.5, 0.3, 0.4, 0.35, 0.5, 0.45, 0.6, 0.7\}$, where $\vec{P}_d = [P_{d1}, P_{d2}, \ldots, P_{dN}]$, $P_{fi} = 0.05$, $i = 1, 2, \ldots, N$. $P = 8$, $P_0 = 0.3$, $\beta = \{1, 100, 600, \infty\}$. The signal to noise ratio is defined as SNR=$10\log_{10}(1/\sigma^2)$ dB. Each curve is obtained by 10^4 Monte Carlo runs.

Figs. 2 and 3 plot the system detection probability (PD) versus SNR of PC-DCM and PC-DCM-CS under given system false alarm probability (PF), respectively. To compare with the existing methods, the performance of likelihood ratio test (LRT) approach which has the best performance among all the rules under the traditional parallel access scheme [5] is also examined. For different values of β, Fig. 4 shows the Receiving Operation Characteristics (ROC) curves of PC-DCM, PC-DCM-CS and LRT.

From the simulation results, we note that under the total power constraint, both PC-DCM and PC-DCM-CS methods can effectively improve the detection performance of the fusion system. From Fig. 2$\sim$ Fig. 4, we observe that the detection performance of PC-DCM and PC-DCM-CS are superior to LRT's. We also observe that the larger the value of β is, the better the performance of the system will be. From Fig. 4, we also note that the performance of PC-DCM is superior to PC-DCM-CS. Obviously, that is because the PC-DCM takes into account the perfect channel gain information, however, the PC-DCM-CS requires only the statistical knowledge of channel gain.

6. CONCLUSION

In this paper, the problem of power constrained partially coherent distributed detection over fading multi-access channel has been studied. Under the total power constraint, the criterion of deflection coefficient maximization has been used to optimize the performance of the fusion system. For partially coherent reception case, the Numerical simulation shows that the proposed PC-DCM and PC-DCM-CS methods can effectively improve the performance of the fusion system.

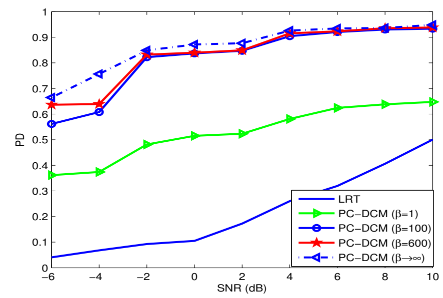

Fig. 2. Comparison of detection probability (PF= 0.05).

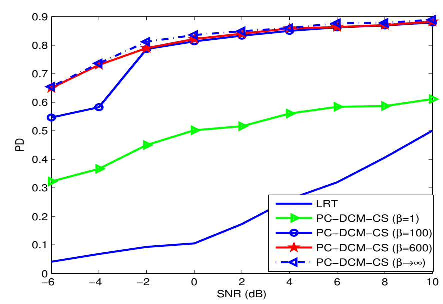

Fig. 3. Comparison of detection probability (PF= 0.05).

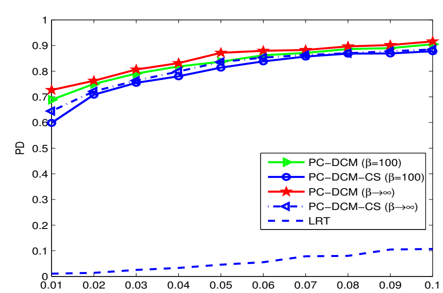

Fig. 4. ROC curves (SNR=0 dB).

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