Journal of Southeast University (English Edition) Vol. 29, No. 4, pp. 355 − 360 Dec. 2013 ISSN 1003—7985

Optimal decision threshold for soft decision cooperative spectrum sensing

Sun Dafei[1,2] Song Tiecheng[1] Wu Ming[1] Hu Jing[1] Guo Jie[1] Gu Bin[1]

([1]National Mobile Communications Research Laboratory, Southeast University, Nanjing 210096, China)

([2]College of Science, Nanjing University of Technology, Nanjing 210009, China)

Abstract: In order to achieve higher spectrum efficiency in cognitive radio (CR) systems, a closed-form expression of the optimal decision threshold for soft decision cooperative spectrum sensing based on the minimum total error probability criterion is derived. With the analytical expression of the optimal decision threshold, the impact of different sensing parameters on the threshold value is studied. Theoretical analyses show that the optimal threshold achieves an efficient trade-off between the missed detection probability and the false alarm probability. Simulation results illustrate that the average signal-to-noise ratio (SNR) and the soft combination schemes have a great influence on the optimal threshold value, whereas the number of samples has a weak impact on the optimal threshold value. Furthermore, for the maximal ratio combing (MRC) and the modified deflection coefficient (MDC) schemes, the optimal decision threshold value increases and approaches a corresponding individual limit value while the number of CR users increases. But the number of CR users has a weak influence on the optimal decision threshold for the equal gain combining (EGC) scheme.

Key words: cognitive radio; cooperative spectrum sensing; energy detection; decision threshold

doi: 10.3969/j.issn.1003 −7985.2013.04.001

The inflexible and fixed spectrum allocation in conventional wireless networks has been shown to encourage under-utilization of the spectrum. The cognitive radio (CR) has emerged as a promising technology to solve this problem through opportunistic access of the spectrum by unlicensed CR users, if non-harmful interference to the licensed primary user (PU) is guaranteed[1]. To ensure that the PUs are sufficiently protected against interference from the CR users, CR users should periodically perform spectrum sensing to obtain reliable results of the PUs' activities[1-2].

Generally, spectrum sensing strategies are categorized into four basic kinds: energy detection, coherent detection, cyclostationary feature detection and eigenvalue-based detection. Due to its simplicity and efficiency, energy detection is recognized as a preferred scheme for practical implementation. To enhance the overall sensing accuracy, cooperation between multiple users is also suggested. Cooperation among CR users is usually cooperated by a fusion center (FC) through two types of fusion rules: hard decision fusion rules [3-4] and soft decision fusion rules [5-6]. In this paper, soft decision fusion rules are investigated, in which accurate energy values observed by different CR users are combined to make a satisfactory decision.

Generally, the performance of spectrum sensing depends greatly on the setting of the decision threshold. Threshold selection can be viewed as an optimization problem. Some research work has been done for this problem based on different objectives in Refs.[7 − 10]. In the Neyman-Pearson framework, the decision threshold is determined by a given target false alarm probability[4,6]. However, detectors under this scheme cannot achieve the minimum total error probability. In Ref.[7], based on the minimum total error rate criterion, the authors discussed the optimal decision threshold for hard decision cooperative spectrum sensing and the optimal decision threshold can be evaluated numerically. The main contribution of this paper is the derivation of a closed-form expression of the optimal decision threshold for soft decision cooperative spectrum sensing, which is based on the minimum total error probability criterion. The impact of different sensing parameters on the optimal decision threshold value is analyzed.

1 System Model

In this section we investigate cooperative spectrum sensing in a centralized CR network which consists of a FC and several CR users. Within the cognitive radio network, each CR user sends its sensing data to the FC periodically through common control channel. Then the FC combines the sensing data from different CR users and makes a decision on the presence or absence of the PU. For simplicity, we assume that the sensing data are sent from the CR user to the FC without any communication

Received 2013-05-02.

Biographies: Sun Dafei(1976—), male, graduate; Song Tiecheng(corresponding author), male, doctor, professor, songtc@seu.edu.cn.

Foundation items: The National Natural Science Foundation of China (No. 61271207, 61372104), the National Science and Technology Major Project (No. 2010ZX03006-002-01), the Specialized Development Foundation for the Achievement Transformation of Jiangsu Province (No. BA2010023).

Citation: Sun Dafei, Song Tiecheng, Wu Ming, et al. Optimal decision threshold for soft decision cooperative spectrum sensing[J]. Journal of Southeast University (English Edition), 2013, 29(4): 355 − 360. [doi: 10.3969/j.issn.1003 −7985.2013.04.001]

channel loss.

Here we consider a CR network with K CR users. Suppose that N samples are utilized for energy detection at each CR user. The spectrum sensing problem at the k-th CR user can be modeled as a binary hypothesis test problem, which is given by

$$x_k = \begin{cases} w_k(n) & \mathrm{H}_0 \\ h_k s(n) + w_k(n) & \mathrm{H}_1 \end{cases} \quad n = 0, 1, \ldots, N-1 \tag{1}$$

where $s(n)$ denotes the primary signal; $w_k(n)$ denotes the additive white Gaussian noise (AWGN); and h_k denotes the channel gain between the PU and the k-th CR user. The channel gain is assumed to be constant during each sensing period. H_0 and H_1 denote the hypotheses corresponding to the absence and presence of the primary signal, respectively.

Besides, we assume that $s(n)$ is considered to be randomly and independently achieved from complex PSK constellations with unit power (i. e., $\|s(n)\|^2 = 1$). Without loss of generality, we suppose that the noise $w_k(n)$ at each sample is a circularly symmetric zero-mean complex Gaussian random variable with unit-variance, and the channel gain h_k is zero-mean complex Gaussian random variable. Thus, the instantaneous signal-to-noise ratio (SNR) of the k-th CR user is $\gamma_k = |h_k|^2$. We assume that FC has prior knowledge of the instantaneous SNR, and this can be realized with direct feedback from the CR users.

The energy detector measures the primary signal energy within a specified duration. Each CR user calculates a summary statistic Y_k over a detection interval of N samples, which is denoted as

$$Y_k = \frac{1}{N}\sum_{n=0}^{N-1} |x_k(n)|^2 \tag{2}$$

Then cooperation diversity of multiple CR users is carried out in order to achieve better spectrum sensing performance.

We first consider local spectrum sensing at the individual CR user. The test statistic of the k-th CR user using energy detection is given by Eq. (2). For simplicity, assuming that N is large enough, local test statistic Y_k approximates the Gaussian distribution according to the central limit theorem, i. e.,

$$Y_k \sim \begin{cases} \mathcal{N}\left(1, \dfrac{1}{N}\right) & \mathrm{H}_0 \\ \mathcal{N}\left(1+\gamma_k, \dfrac{1+2\gamma_k}{N}\right) & \mathrm{H}_1 \end{cases} \tag{3}$$

where $\mathcal{N}(\mu, \sigma^2)$ denotes the Gaussian distribution with the mean value μ and variance σ^2.

We set λ_k as the local decision threshold for the k-th CR user; the local false alarm probability $P_{\mathrm{f},k}$ and the detection probability $P_{\mathrm{d},k}$ can be defined as

$$P_{\mathrm{f},k} = \Pr(Y_k > \lambda_k \mid \mathrm{H}_0) = Q((\lambda_k - 1)\sqrt{N}) \tag{4}$$

$$P_{\mathrm{d},k} = \Pr(Y_k > \lambda_k \mid \mathrm{H}_1) = Q\left((\lambda_k - (1+\gamma_k))\sqrt{\frac{N}{1+2\gamma_k}}\right) \tag{5}$$

where $Q(\cdot)$ denotes the complementary distribution function of the standard Gaussian. Based on the above definitions in Eqs. (4) and (5), the local missed probability $P_{\mathrm{m},k}$ can be defined as

$$P_{\mathrm{m},k} = \Pr(Y_k < \lambda_k \mid \mathrm{H}_1) = 1 - P_{\mathrm{d},k} \tag{6}$$

2 Soft Combination

Cooperation among CR users is usually cooperated by a FC through two types of fusion rules: hard decision fusion rules and soft decision fusion rules. When hard decision fusion rules are used, CR users exchange only one bit of information regarding whether their observed energy value is above a certain threshold or not. In this paper, soft decision fusion rules are investigated in which accurate energy values observed by different CR users are combined to make a better decision. It is demonstrated that soft combination schemes have significant performance improvement over conventional hard combination[5].

For soft combination schemes, sensing data from different CR users is linearly combined with weight coefficients and decisions based on the weighted summation. To allow multiple CR users to collaborate, we transmit the test statistic $\{Y_k\}$ directly to the FC through the common control channel. Once the FC receives $\{Y_k\}$, the global test statistic y_{c} is linearly calculated as[6]

$$y_{\mathrm{c}} = \sum_{k=1}^{K} w_k Y_k \tag{7}$$

where w_k denotes the weight coefficient corresponding to the k-th CR user. The combining weight for the particular user represents its contribution to the global decision. For example, if a CR generates a high SNR signal which may lead to a correct detection on its own, it should be assigned by a larger weight coefficient. For those CR users which experience deep fading or shadowing, their weights should be decreased in order to reduce their negative contribution to the FC.

Assuming that $\{Y_k\}$ and $\{w_k\}$ are independent for different k, then, according to Eq. (7), y_{c} is under the Gaussian distribution. Then the global test statistic has means and variances which are given by

$$\left.\begin{aligned} \mu_0 &= E[y_{\mathrm{c}} \mid \mathrm{H}_0] = \sum_{k=1}^{K} w_k \\ \sigma_0^2 &= \mathrm{var}[y_{\mathrm{c}} \mid \mathrm{H}_0] = \frac{1}{N}\sum_{k=1}^{K} w_k^2 \\ \mu_1 &= E[y_{\mathrm{c}} \mid \mathrm{H}_1] = \sum_{k=1}^{K} w_k(1+\gamma_k) \\ \sigma_1^2 &= \mathrm{var}[y_{\mathrm{c}} \mid \mathrm{H}_1] = \frac{1}{N}\sum_{k=1}^{K} w_k^2(1+2\gamma_k) \end{aligned}\right\} \tag{8}$$

where $E[\cdot]$ and $\mathrm{var}[\cdot]$ denote the statistical expectation and variance, respectively.

The global test statistic is compared with a global decision threshold λ in order to make a global detection result. If $y_c > \lambda$, the FC decides hypothesis H_1 is true; otherwise, the frequency band of interest is assumed not to be used by the PU, so the FC decides hypothesis H_0 is true.

Generally, we set $\sum_{k=1}^{K} w_k = 1$. Then, according to Eq. (8), the global probabilities of the false alarm and detection are given by

$$Q_f = Q\left(\frac{\lambda - \mu_0}{\sigma_0}\right) = Q\left(\frac{\lambda - 1}{\sqrt{\sum_{k=1}^{K} w_k^2}}\sqrt{N}\right) \tag{9}$$

$$Q_d = Q\left(\frac{\lambda - \mu_1}{\sigma_1}\right) = Q\left(\frac{\lambda - (1+\eta)}{\sqrt{\sum_{k=1}^{K} w_k^2(1+2\gamma_k)}}\sqrt{N}\right) \tag{10}$$

where $\eta = \sum_{k=1}^{K} w_k\gamma_k$. The global missed detection probability is given by

$$Q_m = 1 - Q_d = 1 - Q\left(\frac{\lambda - (1+\eta)}{\sigma_1}\right) \tag{11}$$

3 Optimal Decision Threshold Analysis

The essential problem of energy detector design is to determine the decision threshold in order to achieve ideal detection performance. Suppose that we choose a lower decision threshold, so that we will have a higher false alarm probability. On the contrary, if we choose a higher decision threshold, a larger missed detection probability will be achieved. Therefore, there exists a fundamental tradeoff between the probability of false alarm and the probability of missed detection.

Considering the tradeoff between the two error probability, we can know that minimizing the total error probability of spectrum sensing is significant for achieving the better performance of CR systems. For a given frequency band of interest, we define $P(H_1)$ as the probability for which the primary user is present, and $P(H_0)$ as the probability for which the primary user is absent. Obviously, we can obtain $P(H_0) + P(H_1) = 1$. The total error probability P_e is defined as

$$P_e = \alpha Q_f + \beta Q_m \tag{12}$$

where $\alpha = P(H_0)$ and $\beta = P(H_1)$. We assume that the prior probability α is known for all the CR users based on long-term spectrum measurement. By minimizing the total error probability criterion, Q_f and Q_m are weighted and simplified as a measurement of the total error probability. For a special case in which $\alpha = \beta$, the total error probability is calculated as

$$P_e = \frac{1}{2}(Q_f + Q_m) \tag{13}$$

Substituting Q_f in Eq. (9) and Q_m in Eq. (11) into Eq. (12), the total error probability is given by

$$P_e = \alpha Q\left(\frac{\lambda - 1}{\sigma_0}\right) + \beta\left(1 - Q\left(\frac{\lambda - (1+\eta)}{\sigma_1}\right)\right) \tag{14}$$

Therefore, our core goal is to determine the optimal decision threshold which can minimize the total error probability.

Proposition 1 If the decision threshold $\lambda \in (1, 1+\eta)$, then both the false alarm probability Q_f and the missed detection probability Q_m are less than 0.5. Furthermore, let N approach infinity, the false alarm probability $Q_f \to 0$, and the missed detection probability $Q_m \to 0$.

Proof If the decision threshold $\lambda \in (1, 1+\eta)$, then

$$\frac{\lambda - 1}{\sqrt{\sum_{k=1}^{K} w_k^2}}\sqrt{N} > 0, \quad \frac{\lambda - (1+\eta)}{\sqrt{\sum_{k=1}^{K} w_k^2(1+2\gamma_k)}}\sqrt{N} < 0 \tag{15}$$

From Eqs. (9) and (10), according to the monotonicity of the Q function, the detector performance can be derived as

$$Q_f = Q\left(\frac{\lambda - 1}{\sqrt{\sum_{k=1}^{K} w_k^2}}\sqrt{N}\right) < Q(0) = 0.5 \tag{16}$$

$$Q_d = Q\left(\frac{\lambda - (1+\eta)}{\sqrt{\sum_{k=1}^{K} w_k^2(1+2\gamma_k)}}\sqrt{N}\right) > Q(0) = 0.5 \tag{17}$$

Therefore, we can also have

$$Q_m = 1 - Q_d < 0.5 \tag{18}$$

Furthermore, when N approaches infinity, we can obtain

$$\frac{\lambda - 1}{\sqrt{\sum_{k=1}^{K} w_k^2}}\sqrt{N} \to +\infty, \quad \frac{\lambda - (1+\eta)}{\sqrt{\sum_{k=1}^{K} w_k^2(1+2\gamma_k)}}\sqrt{N} \to -\infty \tag{19}$$

Thus, we can also see that $Q_f \to 0$, and $Q_m \to 0$ when N approaches infinity.

In the field of spectrum sensing, a detection probability of 90% and a false alarm probability of 10% are regarded as the target requirements for all the sensing algorithms[4]. From Proposition 1, it follows that the constraints $Q_d > 0.5$ and $Q_m < 0.5$ are equivalent to $1 < \lambda < 1 + \eta$.

Proposition 2 The total error probability P_e is a convex function of the decision threshold λ, when $1 < \lambda < 1$

$+\eta$.

Proof According to Eq. (14), differentiating P_e with respect to λ gives

$$\frac{\partial P_e}{\partial \lambda} = -\frac{\alpha}{\sqrt{2\pi}\sigma_0}\exp\left(-\frac{(\lambda-1)^2}{2\sigma_0^2}\right) + \frac{\beta}{\sqrt{2\pi}\sigma_1}\exp\left(-\frac{(\lambda-(1+\eta))^2}{2\sigma_1^2}\right) \quad (20)$$

Then, the second-order derivative of P_e with respect to λ is given by

$$\frac{\partial^2 P_e}{\partial \lambda^2} = \frac{\alpha(\lambda-1)}{\sqrt{2\pi}\sigma_0^3}\exp\left(-\frac{(\lambda-1)^2}{2\sigma_0^2}\right) + \frac{\beta(\lambda-(1+\eta))}{\sqrt{2\pi}\sigma_1^3}\exp\left(-\frac{(\lambda-(1+\eta))^2}{2\sigma_1^2}\right) \quad (21)$$

If $1<\lambda<1+\eta$, we can see that $\lambda-1>0$, and $\lambda-(1+\eta)<0$. Then the second-order derivative of P_e is greater than 0, that is

$$\frac{\partial^2 P_e}{\partial \lambda^2} > 0 \quad (22)$$

Thus, the total error probability P_e is convex in λ when $1<\lambda<1+\eta$.

From Proposition 2, we can see that the optimal threshold value is unique if it exists. Setting the first derivative as $\frac{\partial P_e}{\partial \lambda}=0$, we can obtain the expression of the optimal threshold as

$$\frac{\alpha}{\sqrt{2\pi}\sigma_0}\exp\left(-\frac{(\lambda-1)^2}{2\sigma_0^2}\right) = \frac{\beta}{\sqrt{2\pi}\sigma_1}\exp\left(-\frac{(\lambda-(1+\eta))^2}{2\sigma_1^2}\right) \quad (23)$$

Solving λ by Eq. (23), the optimal decision threshold is taken to be the largest root. Hence, the optimal decision threshold can be determined by

$$\lambda_{\text{opt}} = \begin{cases} \frac{1}{\sigma_1^2-\sigma_0^2}\left[\sigma_1^2\mu_0 - \sigma_0^2\mu_1 + \sigma_0\sigma_1 \times \sqrt{(\mu_1-\mu_0)^2 + 2(\sigma_1^2-\sigma_0^2)\left(\frac{\ln\sigma}{\ln\beta}+\frac{\ln\sigma_1}{\ln\sigma_0}\right)}\right] & \sigma_0 \neq \sigma_1 \\ \frac{1}{2}(\mu_0+\mu_1) + \frac{\ln\alpha - \ln\beta}{\mu_1-\mu_0}\sigma_0^2 & \sigma_0 = \sigma_1 \end{cases} \quad (24)$$

where $\mu_0=1$, and $\mu_1=1+\eta$. So far, the optimal threshold for soft decision cooperative spectrum sensing is obtained. From Eqs. (8) and (24), we can see that the optimal threshold is a function of the weight coefficients $\{w_k\}$, the number of samples N, and the prior probability α. In the low SNR region, the variances of the global test statistic $\sigma_0^2 \approx \sigma_1^2$. If we assume that the prior probability $\alpha=\beta$, the optimal decision threshold can be simplified as

$$\lambda_{\text{opt}} \approx \frac{\mu_0+\mu_1}{2} = \frac{1+\eta}{2} \quad (25)$$

4 Simulation Results

In this section, simulation results are given to illustrate the impact of system parameters on the optimal threshold value for soft decision cooperative spectrum sensing. Under the Rayleigh fading environment, it is reasonable to assume that we have independent and identically distributed (i. i. d.) Rayleigh fading with the instantaneous SNRs $\gamma_1, \gamma_2, \cdots, \gamma_K$ being i. i. d. exponentially distributed random variables with the mean γ (i. e., the average SNR). The simulation results are obtained from 10^4 realizations for the given constant channel gains.

First, we present the optimal decision threshold for different average SNRs when the equal gain combining (EGC), the maximal ratio combining (MRC), and the modified deflection coefficient (MDC) schemes[6] are adopted. The weight coefficients of the three soft combination schemes can be given as

$$w_{\text{EGC},k} = \frac{1}{K} \qquad 1 \leqslant k \leqslant K \quad (26)$$

$$w_{\text{MRC},k} = \frac{\gamma_k}{\sum_{j=1}^{K}\gamma_j} \qquad 1 \leqslant k \leqslant K \quad (27)$$

$$w_{\text{MDC},k} = \frac{\gamma_k/(1+2\gamma_k)}{\sum_{j=1}^{K}\gamma_j/(1+2\gamma_j)} \qquad 1 \leqslant k \leqslant K \quad (28)$$

Here, we consider a system scenario with the number of CR users $K=4$, the number of samples $N=100$, and the prior probability $\alpha=0.5$. Fig. 1 describes the optimal decision threshold vs. the average SNR γ for three different soft combination schemes according to Eqs. (26), (27) and (28). Fig. 1 shows that the optimal decision threshold is between 1 (lower bound) and $1+\gamma$ (upper bound). It can be also seen that the MRC and MDC schemes have almost the same optimal decision threshold in the low SNR region. Within the high SNR region, the optimal decision threshold for the MRC scheme is greater than that of the MDC scheme. Furthermore, in the low SNR region, the average SNR $\gamma \approx \eta$ and then the optimal decision threshold for the EGC scheme $\lambda_{\text{opt}} \approx 1+\gamma/2$. In addition, Fig. 2 depicts the minimum the total error probability for the corresponding three different soft combination schemes in Fig. 1. From Fig. 2, we can see that both the MRC and MDC schemes have nearly the same performance which outperforms that of the EGC scheme.

Secondly, we consider the impact of the prior probability α on the detector design of the optimal decision threshold. Here, we consider $K=4$, $N=100$, and the average

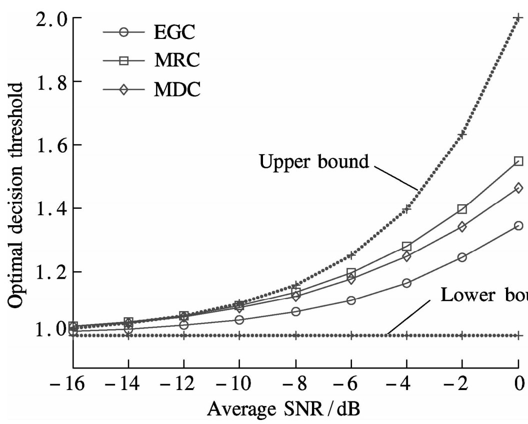

Fig. 1 Optimal decision threshold vs. average SNR with three different soft combination schemes ($K=4$, $N=100$, and $\alpha=0.5$)

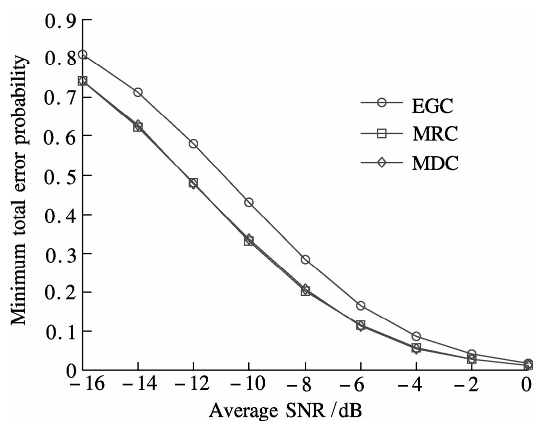

Fig. 2 Minimum total error probability vs. average SNR with three different soft combination schemes ($K=4$, $N=100$, and $\alpha=0.5$)

SNR $\gamma=-6$ dB and -10 dB. Fig. 3 illustrates the relationship between the optimal decision threshold value and the prior probability α. It can be seen from Fig. 3 that the optimal decision threshold increases with the increase in the prior probability α, which means that the activity of the PU has effects on the design of the detector, which is

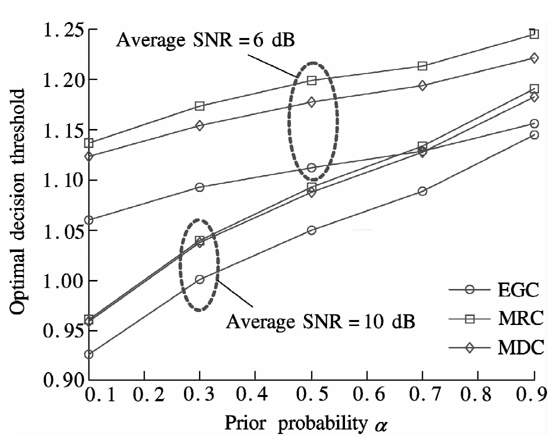

Fig. 3 Optimal decision threshold vs. prior probability with three different soft combination schemes ($K=4$, $N=100$, and the average SNR $=-6$, -10 dB)

reasonable. Since the PU is seldom present (i. e., the prior probability α is large), the optimal decision threshold value should be increased in order to obtain the target minimum the total error probability.

Thirdly, we consider the influence of the number of samples on the optimal decision threshold. We choose $K=4$, $\alpha=0.5$, and the average SNR $\gamma=-6$, -10 dB. Fig. 4 describes the optimal decision threshold vs. the number of samples for three different soft combination schemes. It is verified that the number of samples has almost no influence on the optimal decision threshold. It can also be proved that the optimal threshold of the MRC scheme is greater than that of the MDC scheme. Furthermore, the MRC and MDC schemes have almost the same optimal decision threshold value with the average SNR $\gamma=-10$ dB.

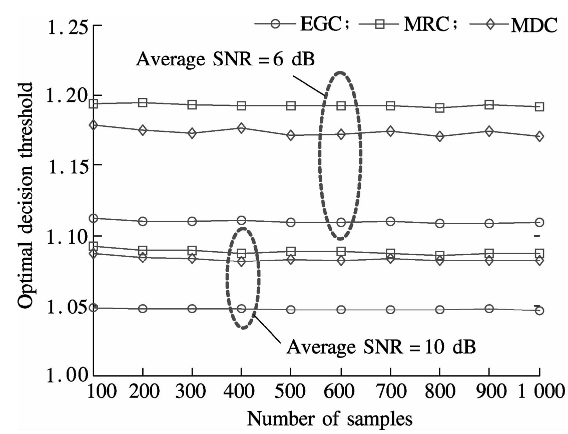

Fig. 4 Optimal decision threshold versus number of samples with three different soft combination schemes with $K=4$, $\alpha=0.5$, and the average SNR $=-6$ dB, -10 dB

Finally, we analyze the impact of the number of CR users on the optimal decision threshold. Here we set $N=100$, $\alpha=0.5$, and the average SNR $\gamma=-6$, -10 dB. Fig. 5 plots the optimal decision threshold vs. the number of CR users for three different soft combination schemes. As the number of the CR user increases, the EGC scheme

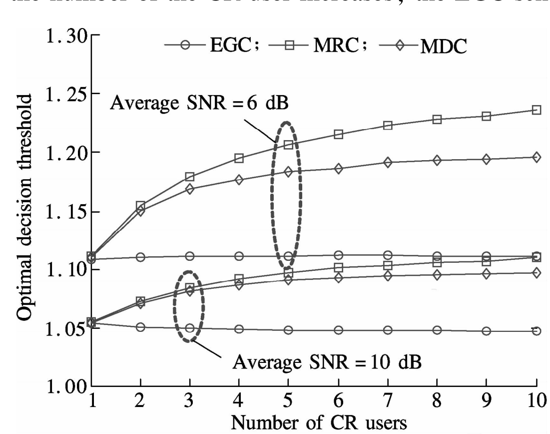

Fig. 5 Optimal decision threshold vs. number of CR users with three different soft combination schemes ($N=100$, $\alpha=0.5$, and the average SNR $=-6$, -10 dB)

has almost the same optimal decision threshold, showing that the number of CR users has a weak influence on the optimal decision threshold for the EGC scheme. However, the optimal decision threshold values of MRC and MDC schemes increase as the number of the CR users increases, and the optimal decision thresholds for the two soft combination schemes approach a corresponding individual limit value while the number of CR users increases.

5 Conclusion

In this paper, a closed-form expression of the optimal decision threshold is derived under the soft decision cooperative spectrum sensing scheme, including several parameters such as the weight coefficients, the prior probability of absence of the PU, the number of samples and the number of CR users. The impacts of these parameters on the optimal decision threshold are verified by detailed simulation results. It is demonstrated that the average SNR of soft combination schemes has a great effect on the value of the optimal decision threshold, whereas the number of samples has a weak influence on the value of the optimal threshold.

References

[1] Liang Y, Chen K, Li G, et al. Cognitive radio networking and communications: an overview [J]. *IEEE Trans Veh Technol*, 2011, **60**(7): 3386 – 3407.

[2] Lu L, Zhou X, Onunkwo U, et al. Ten years of research in spectrum sensing and sharing in cognitive radio [J]. *EURASIP J Wireless Commun Netw*, 2012, **28**(1): 1 – 16.

[3] Ghasemi A, Sousa E. Collaborative spectrum sensing for opportunistic access in fading environments [C]//*Proc IEEE Int Symp on New Frontiers in Dynamic Spectrum Access Networks*. Baltimore, USA, 2005: 131 – 136.

[4] Liang Y, Zeng Y, Peh E, et al. Sensing-throughput tradeoff for cognitive radio networks [J]. *IEEE Trans Wireless Commun*, 2008, **7**(4): 1326 – 1337.

[5] Ma J, Zhao G, Li G. Soft combination and detection for cooperative spectrum sensing in cognitive radio networks [J]. *IEEE Trans Wireless Commun*, 2008, **7**(11): 4502 – 4507.

[6] Quan Z, Cui S, Sayed A. Optimal linear cooperation for spectrum sensing in cognitive radio networks [J]. *IEEE J Sel Topics Signal Process*, 2008, **2**(1): 28 – 40.

[7] Zhang W, Mallik R, Letaief K. Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks [J]. *IEEE Trans Wireless Commun*, 2009, **8**(12): 5761 – 5766.

[8] Fan R, Jiang H, Guo Q, et al. Joint optimal cooperative sensing and resource allocation in multichannel cognitive radio networks [J]. *IEEE Trans Veh Technol*, 2011, **60**(2): 722 – 729.

[9] Luo L, Roy S. Efficient spectrum sensing for cognitive radio networks via joint optimization of sensing threshold and duration [J]. *IEEE Trans Commun*, 2012, **60**(10): 2851 – 2860.

[10] Gong S, Wang P, Huang J. Robust performance of spectrum sensing in cognitive radio networks [J]. *IEEE Trans Wireless Commun*, 2013, **12**(5): 2217 – 2227.

软判决协作频谱感知的最优判决门限

孙大飞[1,2] 宋铁成[1] 吴 名[1] 胡 静[1] 郭 洁[1] 顾 斌[1]

([1] 东南大学移动通信国家重点实验室,南京 210096)
([2] 南京工业大学理学院,南京 210009)

摘要:为了获得认知无线电系统更高的频谱利用效率,基于最小总错误概率准则推导了软判决协作频谱感知最优判决门限的闭合表达式,并且分析了各种频谱感知参数对最优判决门限的影响. 理论分析表明,所提出的最优门限可以获得虚警概率和漏检概率2种性能指标的折中. 从仿真结果可以看出,平均信噪比和软判决方案对最优判决门限影响较大,而样本数量对最优的判决门限几乎无影响. 对于 MRC 和 MDC 两种软判决方案,随着协作用户数量的增加,最优判决门限值随之增加并且趋近于某一极限值. 而对于 EGC 软判决方案,协作用户数对其最优门限值影响很小.

关键词:认知无线电;协作频谱感知;能量检测;判决门限

中图分类号:TN911.23