Adaptive Spatio-Temporal White Space Sensing in Multiple Antenna

Chang-Jun Ahn
Graduate School of Engineering
Chiba University
Chiba, Japan
e-mail:junny@m.ieice.org

***Abstract*—Cognitive radio is an emerging approach to implement efficient reuse of the licensed spectrum by detecting unoccupied spectrum bands and adapting the transmission to those bands while avoiding the interference to primary users. However, rigorous requirements are put on the white space sensing that the secondary user should have the ability to detect the primary signal in very low signal to noise ratio (SNR). To achieve the requirements, in this paper, we discuss the adaptive white space sensing for cognitive radio system based on generalized likelihood-ratio test over Rayleigh fading channel in multiple antennas. The test statistics are based on softly combined spatio-temporal diversity to enhance the detection performance. Additionally, we give the expression of the asymptotic detection performance.**

Keywords–white space sensing; spatio-temporal diversity; cognitive radio; generalized likelihood-ratio test.

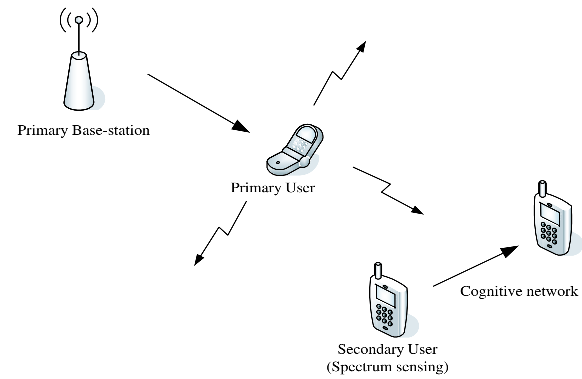

Figure 1. The concept of cognitive radio networks.

I. INTRODUCTION

Spectrum sharing remains one of the most important goals for wireless communication systems. Until this time, the principle has been to assign exclusive frequency bands to different systems or different operators, and systems that used adjacent frequency channels were required to use appropriate spectrum masks to avoid harmful interference with each other. In this case, the spectrum utilization is very limited.

Cognitive radio is an emerging approach to implement efficient reuse of the licensed spectrum by detecting unoccupied spectrum bands and adapting the transmission to those bands while avoiding the interference to primary users as shown in Fig. 1 [1]. This novel approach to spectrum access introduces unique functions at the physical layer: reliable detection of primary users and adaptive transmission over a wide bandwidth [2]-[5].

However, in order to avoid the harmful interference with the primary system, the cognitive radio needs to sense the availability of the spectrum (so called white space). Furthermore, rigorous requirements are put on the spectrum sensing that the secondary user should have the ability to detect the primary signal in very low SNR [6], [7]. Cooperative communication has been known recently as a way to overcome the limitation of wireless system. In some works, the cognitive radios are allowed to cooperate for sensing the spectrum, so that the issues are addressed [8]-[10]. Multiple antenna based cognitive radios are also proposed in [11]-[13].

In this paper, we discuss the adaptive white space sensing for cognitive radio system based on generalized likelihood-ratio test over Rayleigh fading channel in multiple antennas. As the transmitted data and channel impulse response are independent from each other, we can calculate the variability of space and time domains, separately. Although the detection with joint process of the spatio-temporal domains using likelihood ratio test shows the optimum property, it is difficult to give a clear expression of the test statistic. Therefore, the suboptimal method is given with spatio-temporal soft combination of individual test statistics in each domain. Additionally, we give the expression of the asymptotic detection performance. This paper is organized as follows. The white space sensing is described in Section II. In Section III, we describe the adaptive spatio-temporal detection. In Section IV, we show the computer simulation results. Finally, the conclusion is given in Section V.

II. WHITE SPACE SENSING

We assume that the cognitive radio system has been deployed with M received antennas. The channel response between the primary transmitter and the mth antenna of the secondary receiver h_m is modelled as independent and identically distributed (i.i.d.) complex random variables with variance σ_h, and $E(||h_m||^2) = 1$. When band-limited primary signal d_l is transmitted, the received signal at the mth antenna of secondary receiver can be given by

$$y_{m,l} = h_m d_l + n_{m,l}, \tag{1}$$

where $n_{m,l}$ is the additive white Gaussian noise with the variance σ_n^2. In order to avoid the harmful interference with the primary system, the cognitive radio needs to sense the availability of the white space adaptively. The goal of white space

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sensing is to decide between the following two hypotheses:

$$\begin{aligned}\mathcal{H}_0 &: \; y_{m,l} = n_{m,l} \quad \text{(absence of primary signal)} \\ \mathcal{H}_1 &: \; y_{m,l} = h_m d_l + n_{m,l} \quad \text{(presence of primary signal)}.\end{aligned} \tag{2}$$

In the traditional multiple antennas reception, we can combine the signal on each antenna to acquire diversity gain. If h_m and $n_{m,l}$ are known to the secondary receiver, maximum ratio combination (MRC) can be used to maximize the SNR. However, in general, h_m, d_l, and $n_{m,l}$ are unknown in the secondary receiver. Therefore, the case with unknown h_m, d_l, and $n_{m,l}$ is more practical. From this reason, it is reasonable to model d_l as complex Gaussian with zero mean and variance σ_d^2.

III. Adaptive Spatio-temporal Detection

Adaptive detection can be performed with the time-variability of h_m without the knowledge of the noise variance. Reviewing the expression in (1), we find that the variances of d_l and h_m can be transformed to each other without any changes on the distribution of $h_m d_l$. As d_l and h_m are independent from each other, we can calculate the variability of space and time domains, separately. Although the detection with joint process of the spatio-temporal domains using likelihood ratio test shows the optimum property, it is difficult to give a clear expression of the test statistic. Therefore, the suboptimal method is given with spatio-temporal soft combination of individual test statistics in each domain.

A. Spatio variability

Based on the variability of h_m, we get the generalized likelihood-ratio test (GLRT) for the binary hypothesis testing in Eq. (2)

$$\begin{aligned}\Lambda_1 \;&=\; ML \ln \Big(\sum_{m=1}^{M} \sum_{l=1}^{L} |y_{m,l}|^2 \Big) \\ &\quad - L \sum_{m=1}^{M} \ln \Big(\sum_{l=1}^{L} |y_{m,l}|^2 \Big) \\ &\quad - ML \ln (M) \quad \begin{cases} \mathcal{H}_1 & \Lambda_1 \geq \eta \\ \mathcal{H}_0 & \Lambda_1 < \eta \end{cases}\end{aligned} \tag{3}$$

where L is the available independent samples which is smaller than $2BT_c$ where B is the bandwidth, T_c is the coherence time. From the detection theory, the asymptotic distribution of Λ_1 for both hypotheses follows the central and non-central χ^2 distribution of $2M$ degrees of freedom separately. That is

$$2 \cdot \Lambda_1 \sim \begin{cases} \mathcal{X}_{2M}^2 & \text{under } \mathcal{H}_0 \\ \mathcal{X}_{2M}^{\prime 2}(\lambda_1) & \text{under } \mathcal{H}_1 \end{cases} \qquad ML \gg 1 \tag{4}$$

where

$$\lambda_1 = L \cdot \frac{\sigma_d^4}{\sigma_n^4} \cdot \sum_{m=1}^{M} |h_m|^4. \tag{5}$$

where σ_n is the variance of noise $n_{m,l}$.

B. Temporal variability

Similarly, conditioned on the time variability on d_l, the GLR test can be derived with the following result

$$\begin{aligned}\Lambda_2 \;&=\; ML \ln \Big(\sum_{m=1}^{M} \sum_{l=1}^{L} |y_{m,l}|^2 \Big) \\ &\quad - M \sum_{l=1}^{L} \ln \Big(\sum_{m=1}^{M} |y_{m,l}|^2 \Big) \\ &\quad - ML \ln (M) \quad \begin{cases} \mathcal{H}_1 & \Lambda_2 \geq \eta \\ \mathcal{H}_0 & \Lambda_2 < \eta \end{cases}\end{aligned} \tag{6}$$

Likewise, the asymptotic distributions of Λ_2 is

$$2 \cdot \Lambda_2 \sim \begin{cases} \mathcal{X}_{2L}^2 & \text{under } \mathcal{H}_0 \\ \mathcal{X}_{2L}^{\prime 2}(\lambda_2) & \text{under } \mathcal{H}_1 \end{cases} \qquad ML \gg 1 \tag{7}$$

where

$$\lambda_2 = M \cdot \frac{\sigma_h^4}{\sigma_n^4} \cdot \sum_{l=1}^{L} |d_l|^4 \; . \tag{8}$$

where σ_h is the variance of channel h_m.

C. Adapive spatio-temporal soft combination

To fully utilize the observations in space and time variability, adaptive soft combination is performed to maximize the detection performance. The test statistics after combination is given by

$$\Lambda = \omega_1 \Lambda_1 + \omega_2 \Lambda_2 \quad \begin{cases} \mathcal{H}_1 & \Lambda \geq \mu \\ \mathcal{H}_0 & \Lambda < \mu \end{cases} \tag{9}$$

where μ is the detection threshold. The accurate weight can be obtained numerically to get the optimal solution. Moreover, according to the Gaussian approximation of the $\mathcal{X}^2$ distribution (restricted to the limits on the antenna number M in a practical system, this approximation is not quit matched for small M), we have the asymptotic optimal detection with the maximal ratio processing

$$\begin{aligned}\omega_1 &= \frac{L}{\sqrt{M^2 + L^2}}, \\ \omega_2 &= \frac{M}{\sqrt{M^2 + L^2}} \; .\end{aligned} \tag{10}$$

The two test statistics Λ_1 and Λ_2 are thought to be independent from each other due to different variabilities they are base on. Moreover, different Doppler frequency and delay spread of channel show the different coherence time and bandwidth. Therefore, we need to identify the different coherence time and bandwidth. Since L is smaller than $2BT_c$, we need to choose the suitable L, adaptively. Observing Eq. (10), we can get independent optimum weights ω_1 and ω_1 by choosing the suitable L due to different channel variabilities. To derive the more compact expression of the performance, it is common practice to approximate a weighted sum of chi-square variables by that $2 \cdot \Lambda \;\sim\; \alpha \mathcal{X}_{\xi}^2$. The scaling factor α and the effective

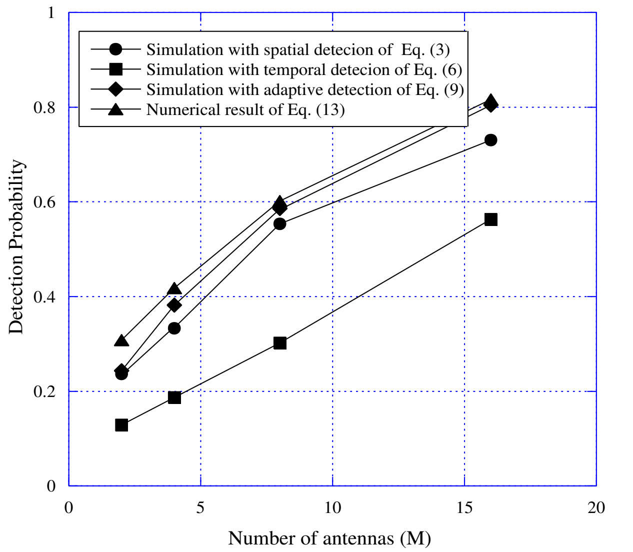

Figure 2. Detection performance for various M with $L = 50$, $P_{FA} = 0.1$ and σ_s^2/σ_n^2=-7dB.

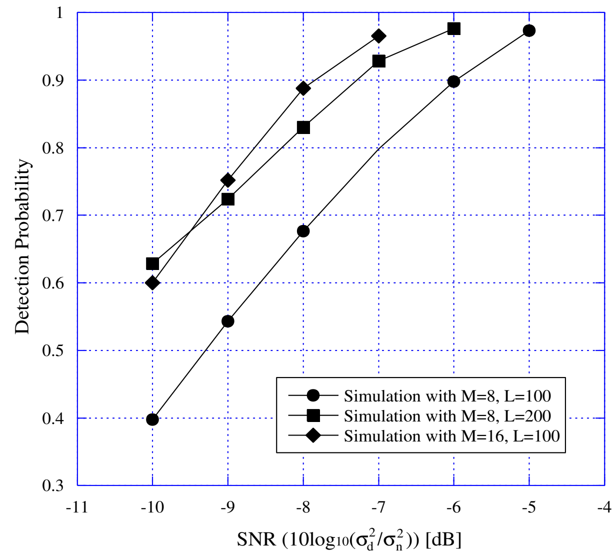

Figure 3. Detection performance for various M and L with $P_{FA} = 0.1$.

degrees of freedom ξ are chosen so that the distribution has the same first two moments as Λ. Thus we have

$$\mathcal{H}_0 \quad : \quad \alpha_1 = \frac{M\omega_1^2 + L\omega_2^2}{M\omega_1 + L\omega_2} \tag{11}$$
$$\xi_1 = \frac{2(M\omega_1 + L\omega_2)^2}{M\omega_1^2 + L\omega_2^2}$$
$$\mathcal{H}_1 \quad : \quad \alpha_2 = \frac{(2M + 2\lambda_1)\omega_1^2 + (2L + 2\lambda_2)\omega_2^2}{(2M + \lambda_1)\omega_1 + (2L + 2\lambda_2)\omega_2}$$
$$\xi_2 = \frac{((2M + \lambda_1)\omega_1 + (2L + \lambda_2)\omega_2)^2}{(2M + 2\lambda_1)\omega_1^2 + (2L + 2\lambda_2)\omega_2^2} .$$

Finally, the approximate probability of false alarm P_{FA} and probability of detection P_D are given by

$$P_{FA} = Q_{x^2_{\xi 1}}(\frac{2\mu}{\alpha_1}) \tag{12}$$
$$P_D = \int_0^\infty\int_0^\infty Q_{x^2_{\xi 2}}(\frac{\alpha_1}{\alpha_2} Q^{-1}_{x^2_{\xi 1}}(P_{FA}))p(\lambda_1)p(\lambda_2)d\lambda_1 d\lambda_2. \tag{13}$$

Obviously, it is easy to get a constant false alarm rate(CFAR) detector in which the detection threshold in Eq. (9) is given by

$$\mu = \frac{1}{2}\alpha_1 Q^{-1}_{x^2_{\xi 1}}(P_{FA}). \tag{14}$$

IV. Computer Simulation Results

Fig. 1 shows the concept of cognitive radio networks to identify the white space. In this section, we consider the received antennas number M to evaluate the detection probability in the cognitive radios based on generalized likelihood ratio test. In general, due to the cost limitation, the multiple antennas communication systems have a few antennas. Therefore, the received antennas number M is less than the samples number L which is only restricted to the detection duration.

Fig. 2 shows the detection performance for various M with $L = 50$, $P_{FA} = 0.1$ and SNR=-7dB. The performance improvement by exploiting two domains of spatio-temporal diversity of the received signal is obvious when M is large ($M \geq 4$). When M is small, the approximation of GLRT is not good enough which leads to bad detection probability. Particularly, the detection performance of adaptive detection is 7% degraded compared with the numerical result when $M = 3$. Moreover, Eq. (13) is given under the assumption that the test statistics in the spatio-temporal domains are independent. Thus the actual correlation will cause larger error when the P_D is large. As a result, the detection performance of adaptive detection and numerical result is the approximately same when the P_D is large.

Fig. 3 shows the detection performance for various M and L with $P_{FA} = 0.1$. From the simulation results, the detection probability is rapidly improved by increasing the number of antennas M and the number of the available independent samples L. Particularly, the detection performance of adaptive detection is more rapidly improved with increasing M than that of with increasing L. There should be a tradeoff between M and L because of the equivalent of spatial and time domains in the detection.

V. Conclusion

We discuss the detection for cognitive radio system over Rayleigh fading channel in multiple antennas. The spatio-temporal diversity is exploited to improve the detection performance. The time variability and the spatial variability are both considered to give better detection performance. The performance improvement by exploiting two domains of spatio-temporal diversity of the received signal is obvious when M is large ($M \geq 4$). When M is small, the approximation of GLRT is not good enough which leads to bad detection probability. Particularly, the detection performance of adaptive detection is 7% degraded compared with the numerical result when $M = 3$. Moreover, the detection performance is more rapidly improved with increasing M than that of with increasing L. However, the number of antennas in a practical system restricts its performance gain that it is only suitable to detect signal in a medium low SNR (greater than -10dB). As the future work, we will adapt the proposed detection method to Google project Loon.

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