ON THE PERFORMANCE OF IN-BAND SENSING WITHOUT QUIET PERIOD IN OFDM SYSTEM

Dong Chen, Jiandong Li, Jing Ma

Broadband Wireless Communications Laboratory, Information Science Institute
State Key Laboratory of Integrated Service Networks, Xidian University, Xian 710071, China
Email: {dchen,jdli,jingma}@mail.xidian.edu.cn

ABSTRACT

In-band spectrum sensing is an effective method of avoiding harmful interference with primary users in cognitive radio. The optimal NoQP Sensing is firstly discussed. Towards a general NoQP Sensing(In-band sensing method without quiet period) problem, we proved that the weighted energy detector is the optimal detector under Neyman-Pearson criterion. The performance of the general NoQP Sensing as well as two NoQP Sensing approaches, Complementary Symbol Couple(CSC) and Self-Signal Suppression(SSS) are analyzed. Based on the optimal NoQP Sensing, we have the performance on detection of the above two methods evaluated. Simulation results show that in the circumstance of IEEE802.22, CSC and SSS have a similar performance, while SSS is more sensitive about the Signal-to-Noise Ratio(SNR).

***Index Terms*—** Cognitive Radio, In-band Sensing, OFDM

1. INTRODUCTION

Spectrum sensing is a crucial problem in cognitive radio(CR) [1] which is a key technology in the future wireless communications.

As the secondary users, cognitive radio can dynamically reuse the temporary vacant spectrum in time domain and spatial domain which will dramatically enhance spectrum efficiency. During this realization of secondary spectrum access, spectrum sensing should be continuously performed to avoid harmful interference with licensed users(referred to as *primary users*). Spectrum sensing is also called channel detection. According to the purpose, there are two types of spectrum sensing [2], Out-of-band sensing and In-band sensing. Out-of-band sensing takes charge of the detection of spectrum besides current channel. From the collected information of spectrum usage, a spectrum pool [3] will be constructed for spectrum management and future spectrum utilization. Once the activity of primary users in current channel presents, In-band sensing should detect such an event with a high probabilityand the system will switch to another idle channel selected from the spectrum pool in finite seconds.

In-band sensing imports more challenges. The interference from the on-going transmission of the secondary users themselves (also called *self-signal*) during In-band sensing makes things complicated. The traditional thinking is the requirement for quiet period [2] to cease transmission during In-band sensing. There are two ways [2],

- Periodically/opportunistically scheduling quiet periods
- Dynamic frequency hopping

Quiet period is an effectual way to give better In-band sensing performance. With quiet perod, various methods for spectrum sensing such as energy detection methods [4] and feature detection methods [3, 5, 6] can be performed.

However, quiet period will bring a lot of overheads and cause frequent interruption to the on-going transmissions. Recently, several approaches to enhance the inefficiency in quiet-period based sensing is proposed by researchers. In-band sensing methods with NO requirement of quiet period will give better transmission performance. In IEEE802.22 [2], Baowei Ji proposed an In-band sensing algorithm based on Self-Signal Suppression (SSS) [7]. The received signal is reconstructed at the receiver according to the estimation of channel and the demodulated signals. Then minus the reconstructed signal from the original received signal to eliminate the effect of interference from the network itself. Another way to perform In-band sensing without quiet period is proposed by Linjun Lv [8]. The interference from the network itself is suppressed with the advantage of orthogonality of the preambles and adjacent OFDM symbols. In [9], Complementary Symbol Couples (CSC) in OFDM are used to filter out secondary signals in detecting primary signals. The proposed scheme measures the power of residual signal at several subcarrier positions and compares it with the predefined threshold to determine the existence of primary user.

The main idea in the above approaches focuses on sensing on the residual signal after the elimination of self-signal. In this paper, we have an analysis on the In-band sensing method

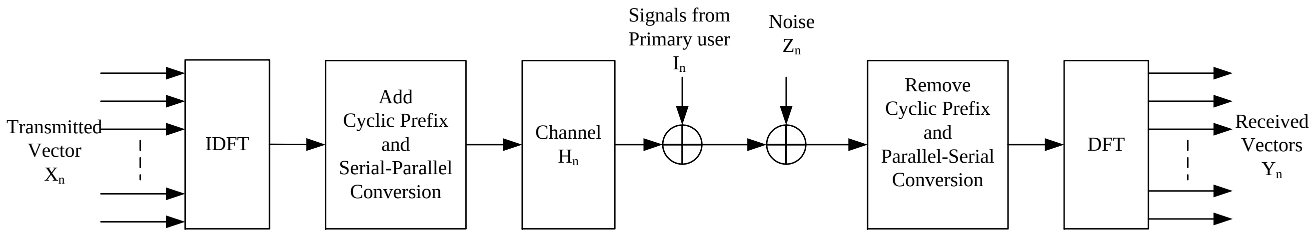

Fig. 1. System Model

without quiet period(NoQP Sensing) problem based on self-signal elimination in Orthogonal Frequency Division Multiplexing(OFDM) system.

The paper is organized as follows. The optimal NoQP Sensing is firstly discussed in section 3. Towards a general NoQP Sensing problem, we proved that the weighted energy detector is the optimal detector under Neyman-Pearson criterion [13]. In section 4, we analyzed the self-signal elimination of two typical methods, CSC and SSS. Based on the optimal NoQP Sensing, we have the performance on detection of the above two methods evaluated. Simulation results show that in the circumstance of IEEE802.22, CSC and SSS have a similar performance, while SSS is more sensitive about the Signal-to-Noise Ratio(SNR).

2. PRELIMINARIES

2.1. Formulation of NoQP Sensing problem

In the NoQP Sensing problem, spectrum sensing is performed on the received signal during data transmission. The secondary users' (SUs) receiver should have the ability to detect the primary users' (PUs) signal with the interference of the on-going transmission from another secondary user's transmitter.

Here we gives a basic model of OFDM system shown in Fig.1 which indicates transmission between the transmitter and receiver of SUs. It should be indicate that those popular NoQP sensing methods are all proposed based on the OFDM system. In this model, subscript n indicates the nth OFDM symbol. $\mathbf{X}_n$ is the transmitted OFDM symbol from secondary transmitter and $\mathbf{Y}_n$ is the received signal at the secondary receiver. Let $\mathbf{H}_n$ denote the channel between the secondary transmitter and receiver. The signal $\mathbf{I}_n$ is the received signal from primary users and is further corrupted by the zero-mean additive white Gaussian noise (AWGN) $\mathbf{Z}_n$.

So the received signal can be expressed as

$$\mathbf{Y}_n = \mathbf{H}_n\mathbf{X}_n + \mathbf{I}_n + \mathbf{Z}_n \tag{1}$$

To robustly detect a primary user, the detector should be able to detect the presence of any possible primary signal that satisfies the power and bandwidth constraint. Here we assume that the primary signal covers all the subcarriers of the OFDM system to simplify the following expression. The situation that subcarriers are partly covered can be easily analyzed in the similar way.

After fading channel, self-signal $\mathbf{H}_n\mathbf{X}_n$ and primary signal $\mathbf{I}_n$ both can be viewed as independent complex gaussian random vector with zero means. Their covariance matrices are $\mathbf{C_X}$ and $\mathbf{C_I}$.

$$\mathbf{C_X} = \begin{pmatrix} \delta_{11}^2 & \cdots & \delta_{M1}^2 \\ \vdots & \ddots & \vdots \\ \delta_{1M}^2 & \cdots & \delta_{MM}^2 \end{pmatrix} \tag{2}$$

in which $\delta_{ij}^2 = \delta_{ji}^2 = X_{n,i}X_{n,j}\mathrm{Cov}[H_{n,i}, H_{n,j}]$.

So $\mathbf{C_X}$ is a weighted covariance matrix of the channel $\mathbf{H}_n$. We assume the components of $\mathbf{I}_n$ are independent which means that $\mathbf{C_I}$ is a diagonal matrix. Actually, correlation among the components of $\mathbf{I}_n$, e.g. due to multipath channel memory effect, will only improve the sensing performance [10]. The local noise $\mathbf{Z}_n$ is independent complex gaussian random vector. The real and imaginary parts of its components are independent and identically distributed gaussian random variables with zero means. The covariance matrix of $\mathbf{Z}_n$ is $\mathbf{C_Z}$.

During secondary spectrum access, in order to guarantee noninterference with potentially hidden primary receivers, the secondary user need to be able to detect very week primary signals. Here we assume that the primary user is far away from the secondary users. Due to the fading channel, the received primary signal is rather low that it may be buried in the local noise. So in such a situation, the secondary users's transmission is decodable.

Hence, we form the following binary hypotheses test for spectrum sensing according to (1). Hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ indicate the event that the primary user is absent or present, respectively.

$$\begin{aligned} \mathcal{H}_0 &: \mathbf{Y}_n = \mathbf{H}_n\mathbf{X}_n + \mathbf{Z}_n \\ \mathcal{H}_1 &: \mathbf{Y}_n = \mathbf{H}_n\mathbf{X}_n + \mathbf{I}_n + \mathbf{Z}_n \end{aligned} \tag{3}$$

We emphasize that the self-signal $\mathbf{H}_n\mathbf{X}_n$ will not appear in the quiet period. This is the main difference between quiet-period based sensing and NoQP sensing.

2.2. Self-signal Elimination

The primary signal intensity is much lower than the secondary signal's. Obviously, the existance of secondary signal will have negative effect on In-band sensing. The basic idea of NoQP sensing is to eliminate the self-signal before detection which will make the test statistic more clean. This self-signal elimination operation can be done with the proposes provided in [7, 8] or method shown in [9].

No matter which algorithm is used, after self-signal elimination the test hypotheses (3) can be rewritten in the following form

$$\begin{aligned} \mathcal{H}_0 &: \mathbf{Y}_n = \mathbf{R}_n + \mathbf{Z}_n \\ \mathcal{H}_1 &: \mathbf{Y}_n = \mathbf{R}_n + \mathbf{I}_n + \mathbf{Z}_n \end{aligned} \tag{4}$$

$\mathbf{R}_n$ indicates the remaining signal after the processing to suppress the self-signal. It should be a function of $\mathbf{X}_n$ and may be different for hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$. Let $\mathbf{C}_{\mathbf{R}0}$ denote the covariance matrix of $\mathbf{R}_n$ under $\mathcal{H}_0$ and $\mathbf{C}_{\mathbf{R}1}$ denote the covariance matrix of $\mathbf{R}_n$ under $\mathcal{H}_1$. Generally, the smaller $\mathbf{C}_{\mathbf{R}0}$ and $\mathbf{C}_{\mathbf{R}1}$ are, the better sensing performance can be achieved.

A special case is $\mathbf{R}_n = \mathbf{H}_n\mathbf{X}_n$ when no processing is performed.

3. OPTIMAL IN-BAND SENSING WITHOUT QUIET PERIOD

In this section, we will talk about the optimal sensing method based on the model we proposed in the above section. We assume that the primary user characteristics is not known except the bandwidth. It means that no feature detection [2] will be used.

In many practical situations, it is difficult to assign realistic costs and a priori probabilities for each decision under Bayes criterion [13]. Neyman-Pearson criterion is popular in such situations. Under Neyman-Pearson criterion, the performance is evaluated with two conditional probabilities, probability of false alarm P_F and probability of detection P_D. The optimal decision rule is given by the following Likelihood Ratio Test(LRT).

$$\Lambda(\mathbf{Y}_n) = \frac{f(\mathbf{Y}_n|H_1)}{f(\mathbf{Y}_n|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta \tag{5}$$

The quantity on the left-hand side is the likelihood ratio, and on the right-hand side η is the optimum threshold for given probability of false alarm P_F.

$\mathbf{R}_n$, $\mathbf{I}_n$ and $\mathbf{Z}_n$ are independent with each other. We have the probability density function of the received signal under $\mathcal{H}_0$ and $\mathcal{H}_1$ shown as

$$\begin{aligned} & f(\mathbf{Y}_n|H_0) \\ &= \frac{1}{\pi^M \det(\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})} \exp\left(-\mathbf{Y}_n^H (\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})^{-1} \mathbf{Y}_n\right) \end{aligned} \tag{6}$$

$$\begin{aligned} & f(\mathbf{Y}_n|H_1) \\ &= \frac{1}{\pi^M \det(\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})} \times \\ & \qquad \exp\left(-\mathbf{Y}_n^H (\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})^{-1} \mathbf{Y}_n\right) \end{aligned} \tag{7}$$

From the assumption given in section2.1, we notice that $\mathbf{C}_{\mathbf{I}}$ and $\mathbf{C}_{\mathbf{Z}}$ are diagonal matrices. And $\mathbf{C}_{\mathbf{R}0}$ and $\mathbf{C}_{\mathbf{R}1}$ are symmetric matrices. As a result, $(\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})^{-1}$ and $(\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})^{-1}$ are both symmetric.

Let

$$\mathbf{K} = (\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})^{-1} - (\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})^{-1} \tag{8}$$

In the condition that $\mathbf{C}_{\mathbf{R}}$ is a diagonal matrix which indicates the components in $\mathbf{R}_n$ are all independent, $\mathbf{K}$ is a diagonal matrix.

Substitute (6) and (7) into (5), one obtains

$$\begin{aligned} & \Lambda(\mathbf{Y}_n) = \frac{f(\mathbf{Y}_n|H_1)}{f(\mathbf{Y}_n|H_0)} \\ &= \frac{\pi^M \det(\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})}{\pi^M \det(\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})} \times \\ & \exp\left(-\mathbf{Y}_n^H ((\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})^{-1} - (\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})^{-1}) \mathbf{Y}_n\right) \\ &= \frac{\det(\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})}{\det(\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})} \exp\left(\mathbf{Y}_n^H \mathbf{K} \mathbf{Y}_n\right) \end{aligned} \tag{9}$$

Take the natural logarithm on both sides of (5) and rearrange the equation, the LRT becomes

$$\mathbf{Y}_n^H \mathbf{K} \mathbf{Y}_n \underset{H_0}{\overset{H_1}{\gtrless}} \ln\eta + \ln\frac{\det(\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})}{\det(\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})} \tag{10}$$

As $\mathbf{Y}_n^H\mathbf{Y}_n$ indicates the energy of $\mathbf{Y}_n$, we view $\mathbf{Y}_n^H\mathbf{K}\mathbf{Y}_n$ a weighted signal energy similarly. According to (10), We get the following throrem.

Theorem 1 *The optimal detector in general NoQP sensing is weighted energy detector shown as*

$$\mathbf{Y}_n^H \mathbf{K} \mathbf{Y}_n \underset{H_0}{\overset{H_1}{\gtrless}} \eta' \tag{11}$$

where $\mathbf{K} = (\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})^{-1} - (\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})^{-1}$ *and* $\eta' = \ln\eta + \ln\frac{\det(\mathbf{C}_{\mathbf{R}1} + \mathbf{C}_{\mathbf{I}} + \mathbf{C}_{\mathbf{Z}})}{\det(\mathbf{C}_{\mathbf{R}0} + \mathbf{C}_{\mathbf{Z}})}$.

When multiple OFDM symbols, e.g. N OFDM symbols, are used in the detection, the analysis is similar. The difference is that the covariance matrices of the signals are more complex and the dimension changes from $M \times M$ to $NM \times NM$.

4. PERFORMANCE EVALUATION

From theorem 1, the detection performance of the optimal detector is related to the the covariance matrices $\mathbf{C}_{\mathbf{R}0}$ and $\mathbf{C}_{\mathbf{R}0}$ after self-signal elimination.

In literature [7] and [9], two spectrum sensing method is proposed based on self-signal elimination, which is

- Sensing with complementary symbols couple
- Sensing with channel estimation

Different self-signal elimination methods leads to different residual signal. So it is necessarily to give further research on the detection performance based on these practical self-signal elimination methods.

4.1. The case of CSC

In [9], complementary symbol couple is used to eliminate self-signals. The complementary symbol couple is defined as

$$\mathbf{X}_n + \mathbf{X}_{n+1} = \mathbf{0} \tag{12}$$

At the receiver, signals on complementary symbol couple are added by $\mathbf{Y}_n + \mathbf{Y}_{n+1}$ to eliminate self-signal. In statistic meaning, the test hypotheses changes from (3) to

$$\begin{aligned} \mathcal{H}_0 : \mathbf{Y}_n &= \frac{1}{\sqrt{2}}(\mathbf{H}_n - \mathbf{H}_{n+1})\mathbf{X}_n + \mathbf{Z}_n \\ \mathcal{H}_1 : \mathbf{Y}_n &= \frac{1}{\sqrt{2}}(\mathbf{H}_n - \mathbf{H}_{n+1})\mathbf{X}_n + \mathbf{I}_n + \mathbf{Z}_n \end{aligned} \tag{13}$$

in which

$$\mathbf{R}_n = \frac{1}{\sqrt{2}}(\mathbf{H}_n - \mathbf{H}_{n+1})\mathbf{X}_n \tag{14}$$

From the above equation, one can learn that the residual signal $\mathbf{R}_n$ is directly determined by the channel vector. In an ideal situation in which channel keeps the same between adjacent OFDM symbols, $\frac{1}{\sqrt{2}}(\mathbf{H}_n - \mathbf{H}_{n+1})\mathbf{X}_n = \mathbf{0}$, the self-signal can be completely eliminated.

In a practical environment, the fading channel model based on first-order AR model can be given in the form [11]

$$\mathbf{H}_{n+1} = \sqrt{\alpha}\mathbf{H}_n + \sqrt{1-\alpha}\mathbf{W}_{n+1} \tag{15}$$

where $\mathbf{H}_n$ and $\mathbf{W}_{n+1}$ are independent identically distributed complex Gaussian random vectors.

Substitute (15) into (14), one gets the residual signal

$$\begin{aligned} \mathbf{R}_n &= \frac{1}{\sqrt{2}}(\mathbf{H}_n - \mathbf{H}_{n+1})\mathbf{X}_n \\ &= \frac{1}{\sqrt{2}}(1-\sqrt{\alpha})\mathbf{H}_n\mathbf{X}_n - \frac{1}{\sqrt{2}}\sqrt{1-\alpha}\mathbf{W}_{n+1}\mathbf{X}_n \end{aligned} \tag{16}$$

Further we can easily obtain

$$\mathbf{C}_{\mathbf{R}0} = \mathbf{C}_{\mathbf{R}1} = (1-\sqrt{\alpha})\mathbf{C}_{\mathbf{X}}. \tag{17}$$

According to the Jakes' model [14]

$$\alpha = J_0(2\pi t f)^2 \tag{18}$$

where $J_0(\cdot)$ is the zero-order Bessel function of the first kind. $f = f_d T_s$, f_d is the maximum Doppler frequency in the fading environment, and T_s is the sampling period. In OFDM, t is the sample number in an OFDM symbol.

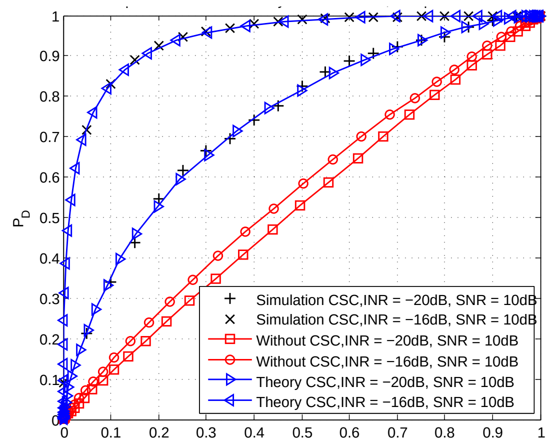

Fig. 2. Receiver operating characteristics curves

Fig.2 shows the receiver operating characteristics(ROC) [13] curves of the optimal detector in Theorem1 with the CSC as the self-signal elimination method. The curves are obtained with Monte Carlo simulations which is generally used in the evaluation of LRT-based detectors.

The simulation environment is based on an IEEE802.22 system. The channel used in this simulation refers from IEEE 802.22 documents [12]. $t \times T_s = 308\mu sec$ (GI = 1/32) and f_d =2.5Hz.

Here we define

$$\text{SNR} = \frac{\text{Secondary user signal}}{\text{Noise}}$$

and

$$\text{INR} = \frac{\text{Primary user signal}}{\text{Noise}}$$

In Fig.2, the blue and red solid line curves indicate the ROCs of the optimal detector with or without CSC respectively. Obviously, remarkable improvement on P_D is achieved with CSC for a given P_F. It means self-signal elimination can actually improve the detection performance. Meanwhile, we also show the ROCs given in [9] as the black cross and plus markers. As the method given in [9] is also an energy detector, its ROC curves show a similar performance as the red solid line.

4.2. The case of SSS

Another propose to eliminate the self-signal is given in [7]. Its In-band sensing scheme with channel estimation is shown in fig.3.

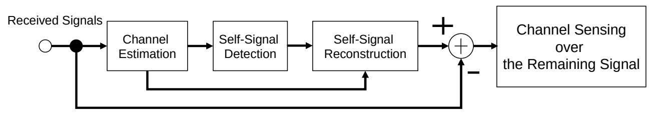

Fig. 3. The scheme of sensing with channel estimation

The received signal is reconstructed at the receiver according to the estimation of channel and the demodulated signals. Then minus the reconstructed signal from the original received signal to eliminate self-signal.

Let $\tilde{\mathbf{H}}_n$ denotes the estimation of $\mathbf{H}_n$. Refers from the principle in Fig.3, the original test hypotheses changes to

$$\begin{aligned}\mathcal{H}_0 &: \mathbf{Y}_n = (\mathbf{H}_n\mathbf{X}_n - \tilde{\mathbf{H}}_n\mathbf{X}_n) + \mathbf{Z}_n \\ \mathcal{H}_1 &: \mathbf{Y}_n = (\mathbf{H}_n\mathbf{X}_n - \tilde{\mathbf{H}}_n\mathbf{X}_n) + \mathbf{I}_n + \mathbf{Z}_n \end{aligned} \tag{19}$$

in which the residual signal

$$\mathbf{R}_n = \mathbf{H}_n\mathbf{X}_n - \tilde{\mathbf{H}}_n\mathbf{X}_n \tag{20}$$

The estimation of $\mathbf{H}_n$ can be viewed as estimation of $\mathbf{H}_n\mathbf{X}_n$ for constant $\mathbf{X}_n$. So we let $\mathbf{G}_n = \mathbf{H}_n\mathbf{X}_n$, and $\tilde{\mathbf{G}}_n$ denotes the estimation of $\mathbf{G}_n$. The covariance matrix of $\mathbf{G}_n$ is $\mathbf{C}_\mathbf{X}$ given in section 2.1. We should announced that usually used Least Square(LS) [15] channel estimation algorithm can not satisfy the requirement in (19). After self-signal elimination with LS, one will always get $\mathbf{Y}_n = \mathbf{0}$ under both test hypotheses.

The estimation performance will not lower than the Cramer-Rao Lower Bound(CRLB) [16] for any unbiased channel estimation. CRLB indicates lower bound of an unbiased estimation. If the "regularity" condition is satisfied, the covariance of any unbiased estimation $\tilde{\mathbf{G}}_n$ follows

$$E\left[\left(\tilde{\mathbf{G}}_n - \mathbf{G}_n\right)\left(\tilde{\mathbf{G}}_n - \mathbf{G}_n\right)^H\right] \geq \mathbf{J}^{-1}(\mathbf{G}_n) \tag{21}$$

where $\mathbf{J}(\mathbf{G}_n)$ is Fisher Information Matrix(FIM).

$E[(\tilde{\mathbf{G}}_n - \mathbf{G}_n)(\tilde{\mathbf{G}}_n - \mathbf{G}_n)^H]$ is the covariance matrix of the residual signal $\mathbf{R}_n$ which are $\mathbf{C}_{\mathbf{R}0}$ and $\mathbf{C}_{\mathbf{R}1}$ under each hypothesis. So CRLB gives the lower bound of self-signal elimination performance.

Under the hypothesis $\mathcal{H}_0$, the joint probability density function of $\mathbf{Y}_n$ and $\mathbf{G}_n$ is

$$\begin{aligned} &f(\mathbf{Y}_n, \mathbf{G}_n) = f(\mathbf{Y}_n|\mathbf{G}_n)f(\mathbf{G}_n) \qquad (22)\\ &= \lambda \exp\left(-(\mathbf{Y}_n - \mathbf{G}_n)^H\mathbf{C}_\mathbf{Z}^{-1}(\mathbf{Y}_n - \mathbf{G}_n) - \mathbf{G}_n^H\mathbf{C}_\mathbf{X}^{-1}\mathbf{G}_n\right)\end{aligned}$$

where $\lambda = \frac{1}{\pi^{2M}\det(\mathbf{C}_\mathbf{Z})\det(\mathbf{C}_\mathbf{X})}$ is a constant and will not affect our following analysis.

As $\mathbf{G}_n$ and $\mathbf{Y}_n$ has zero means, it can be proved that the "regularity" condition can be satisfied due to

$$\begin{aligned} &E\left[\frac{\partial}{\partial \mathbf{G}_n}\ln f_{Y,G}(\mathbf{Y}_n, \mathbf{G}_n)\right] \\ &= E\left[-\mathbf{C}_\mathbf{Z}^{-1}\mathbf{Y}_n - (\mathbf{C}_\mathbf{Z}^{-1} + \mathbf{C}_\mathbf{X}^{-1})\mathbf{G}_n\right] \\ &= \mathbf{0} \end{aligned} \tag{23}$$

So the FIM can be calculated by

$$\begin{aligned}\mathbf{J}(\mathbf{G}_n) &= -E\left[\frac{\partial^2}{\partial^2 \mathbf{G}_n}\left(-(\mathbf{Y}_n - \mathbf{G}_n)^H\mathbf{C}_\mathbf{Z}^{-1}(\mathbf{Y}_n - \mathbf{G}_n) - \right.\right. \\ &\qquad \left.\left. \mathbf{G}_n^H\mathbf{C}_\mathbf{X}^{-1}\mathbf{G}_n\right)\right] \\ &= \mathbf{C}_\mathbf{Z}^{-1} + \mathbf{C}_\mathbf{X}^{-1} \end{aligned} \tag{24}$$

From (21) and (24) we get the CRLB which is the covariance matrix of $\mathbf{R}_n$.

$$\begin{aligned}\mathbf{C}_{\mathbf{R}0} &= E\left[\left(\tilde{\mathbf{G}}_n - \mathbf{G}_n\right)\left(\tilde{\mathbf{G}}_n - \mathbf{G}_n\right)^H\right] \\ &\geq \mathbf{J}^{-1}(\mathbf{G}_n) = \left(\mathbf{C}_\mathbf{Z}^{-1} + \mathbf{C}_\mathbf{X}^{-1}\right)^{-1} \end{aligned} \tag{25}$$

Similarly, the CRLB under $\mathcal{H}_1$ is

$$\mathbf{C}_{\mathbf{R}1} \geq \left((\mathbf{C}_\mathbf{I} + \mathbf{C}_\mathbf{Z})^{-1} + \mathbf{C}_\mathbf{X}^{-1}\right)^{-1} \tag{26}$$

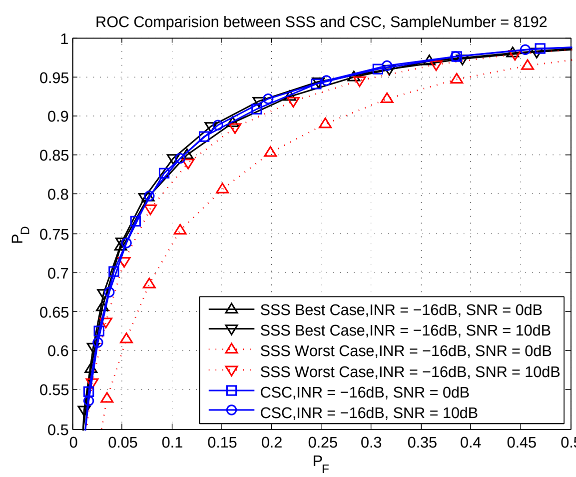

Fig. 4. ROC Comparison under different SNRs

Here we have the performance of optimal detector with SSS as self-signal elimination method evaluated in fig.4 and fig.5. The simulation environment and method are the same as the previous subsection.

Figure 4 shows the ROC comparison between CSC and SSS under different SNRs. According to different training sequence which leads to different weight of $\mathbf{C}_\mathbf{X}$, we gives the best and worst performance of SSS. It can be learned that SNR has obvious effect on SSS. At low SNR, such as 0dB, its worst performance is much lower than CSC. However, as the SNR increases, these two methods has a similar performance.

Given SNR as 10dB, fig.5 shows the effect of INR on the performance. The curve of CSC lies between the best case and worst case of SSS. As such a SNR is more practical, we learn that the performance of both methods are similar actually.

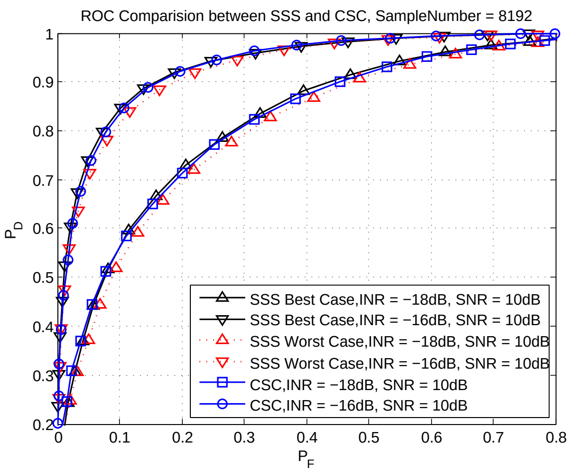

Fig. 5. ROC Comparison under different INRs

5. CONCLUSION

We have the In-band spectrum sensing without quiet period problem in cognitive radio discussed in this paper. We show that the weighted energy detector is the optimal detector under Neyman-Pearson criterion. Based on this optimal detector, we evaluated the self-signal elimination performance of two NoQP Sensing approaches, Complementary Symbol Couple(CSC) and Self-Signal Suppression(SSS). Further Evaluation results indicate that they have similar performance in IEEE802.22 environment while SSS is more sensitive about the Signal-to-Noise Ratio(SNR).

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