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An Improved Spectrum Sensing Technique using Matched Filter Detection with a NP Observer

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Abstract
The growing demand of wireless applications has put a lot of constraints on the usage of available radio spectrum which is a limited and precious resource. Some frequency bands in the spectrum are largely unoccupied most of the time and some other frequency bands are partially occupied. This underutilization of radio spectrum is minimized by using the Cognitive radio[1]. An important requirement of the Cognitive Radio is to sense the spectrum holes. The spectrum sensing function enables the CR to adapt its environment by detecting the primary users that are receiving data within the communication range of CR user. We can find various spectrum sensing techniques [1-2] which, in general could be classified as energy based sensing, matched filter-based sensing, cyclostationary feature-based sensing and so on. Different techniques serve different purpose based on their advantages and disadvantages. The matched filter-based detect gives better detection compared with the other methods; however, it requires complete signal information.
In this paper, we proposed a new approach of matched filter-based spectrum sensing with a Neyman-Pearson observer and we observed that, this approach gives better probability detection and threshold values than the matched filter-based spectrum sensing with a Log-Likelihood Ratio test.

Keywords
Cognitive Radio, Receiver Operating Characteristics, Signal to Noise Ratio, Matched Filter, Neyman Pearson Observer

I. Introduction
The recent trend in Cognitive Radio-related research has altered a great deal of interest in spectrum sensing and detection of radio users in the environment. The key objective behind spectrum sensing and detection is to maximize the probability of detection without losing much on the probability of false alarm while minimizing the complexity and time to sense/detect the radio. In literature, one, can find various spectrum sensing techniques which, in general, could be classified as (1) energy-based sensing, (2) cyclostationary feature-based sensing, (3) Matched filter-based sensing and (4) other sensing techniques. The energy-based sensing is the simplest method to sense the environment in a blind manner; the cyclostationary-based sensing may require some information about the spectral-user signal characteristics; and the matched filter-based sensing requires the complete information of the spectral user signal.
In this paper, we present the matched filter-based method with log-likelihood test and neyman-peasrson observer spectrum sensing.
Let us define the signal model to be used. We define two hypotheses H_0 and H_1 to represent the present of radio signal, the corresponding signal model is

$$x(t)=\begin{cases} w(t); & under\, H_0 \\ s(t)+w(t); & under\, H_1 \end{cases} \quad (1)$$

Where x(t) is the complex baseband of the sensed radio signal, s(t) is the received primary user signal, w(t) is the Additive White Gaussian Noise with a zero mean and noise power of σ^2.
Let us consider H_0 and H_1 are binary hypotheses, and D_0 and D_1 are statistical decisions and the probability density functions are

$$f(x/H_i), i=0,1 \quad (2)$$

The possible outcomes of binary experiment are:

$$D_0/H_0 : Correct\, decision\, or\, Correct\ Dismissal$$
$$D_1/H_0 : Type-I\ Error\ or\ False\ Alarm$$
$$D_0/H_1 : Type-II\ Error\ or\ False\, Dismissal$$
$$D_1/H_1 : Correct\, decision\ or\ Correct\, Detection$$

From the fig. 1, probability of errors and correct decisions are defined as

$$\Pr obability\ of\ Flase\ Alarm = P_{FA} = \int_{\gamma}^{\infty} f(x/H_0)dx \quad (3)$$

$$\Pr obability\ of\ Dismissal = 1-P_{FA} = \int_{-\infty}^{\gamma} f(x/H_0)dx \quad (4)$$

$$\Pr obability\ of\ Detection = P_D = \int_{\gamma}^{\infty} f(x/H_1)dx \quad (5)$$

$$\Pr obability\ of\ Flase\ Dismissal = 1-P_D = \int_{-\infty}^{\gamma} f(x/H_1)dx \quad (6)$$

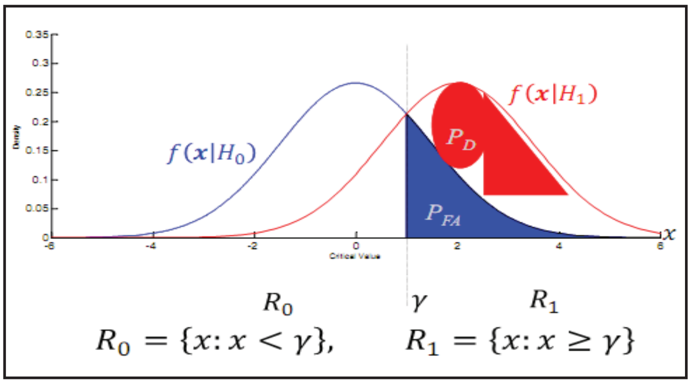

Fig. 1: Observation Space

II. Matched Filter Detection
The matched filter detection based spectrum sensing is exactly the same as the traditional matched filter detection technique deployed as in digital receiver. Obviously for matched filter-based spectrum sensing a complete knowledge of the primary user signal is required (such as the modulation format, data rate, carrier frequency , pulse shape etc) [6].

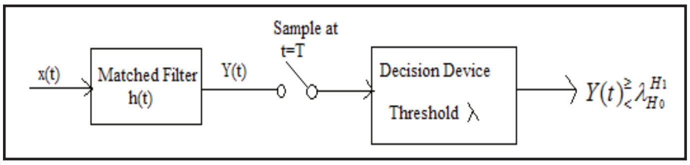

Fig. 2: Block Diagram of Linear Matched Filter

The Signal to Noise ratio at the output of the matched filter is

$$(SNR)_o = 2/N_o \int_{-\infty}^{\infty} |S(f)|^2\, df \tag{7}$$

Where N_0 is the channel Noise,$(SNR)_0$ is channel Signal to Noise Ratio. S (f) is the Fourier transform of the signal S(t) to which the filter is matched. Using the Raleigh's energy theorem we may write the signal energy

$$E = \int_{-\infty}^{\infty} S^2(t)dt = \int_{-\infty}^{\infty} |S(f)|^2\, df \tag{8}$$

Therefore, the output Signal to Noise ratio of the matched filter can be as

$$(SNR)_o = 2E/N_o \tag{9}$$

Where E is the part of the signal energy have been received by the filter at time t=T. Thus the output Signal to Noise ratio of the matched filter depends on the ratio of the signal energy to power Spectral density of White noise.

Spectrum Sensing using matched filter can be obtained by the following steps:

1. The output of the matched filter is sampled at time t=T.
2. The amplitude of the sampled signal is compared with a given threshold λ.
3. If the amplitude of the sampled output is greater than the threshold value, the receiver decides that the primary known signal S(t) is present. Otherwise, the receiver decides that the signal is absent.

Hence the decision is only depends on the amplitude of the impulse signal but on duration of the Signal [2].

III. Caluclation of Threshold Value

A. Likelihood Ratio Test

Assuming that, at time t, we receive a signal x(t). Knowing the probabilities are $f(x/H_0)$ and $f(x/H_1)$, we can calculate the likelihood ratio as

$$\lambda(x) = \frac{f(x/H_1)}{f(x/H_0)} = \frac{p_1(x)}{p_0(x)} \tag{10}$$

And compare it to a threshold value

$$\lambda_0 = \frac{p(H_0)}{p(H_1)} \tag{11}$$

Where $p(H_0)$ and $p(H_0)$ are priori probabilities

The decision can be taken as accordingly

$$\lambda(x) = \begin{cases} \geq \lambda_0; & Choose\, H_1 \\ < \lambda_0; & Choose\, H_0 \end{cases} \tag{12}$$

B. Neyman-Pearson Observer

To obtain threshold value using Neyman-Pearson observer, we are using Log-Likelihood ratio test, assuming the we know the complete information about the primary user.

The likelihood ratio is defined as

$$\lambda(x) = \frac{f(x/H_1)}{f(x/H_0)} = \underset{D_0}{\overset{D_1}{\gtrless}} \gamma \tag{13}$$

Where $x = [x(0)\, x(1) \ldots\ldots x(N-1)]^T$ and γ is threshold value

$$f(x/H_1) = (2\pi\sigma^2)^{-N/2} \exp\left(-\frac{(x-s)^T(x-s)}{2\sigma^2}\right) \tag{14}$$

$$f(x/H_0) = (2\pi\sigma^2)^{-N/2} \exp\left(-\frac{x^T x}{2\sigma^2}\right) \tag{15}$$

Form equation (13), (14) and (15)

$$\lambda(x) = \frac{(2\pi\sigma^2)^{-N/2} \exp\left(-\frac{(x-s)^T(x-s)}{2\sigma^2}\right)}{(2\pi\sigma^2)^{-N/2} \exp\left(-\frac{x^T x}{2\sigma^2}\right)}$$

$$\lambda(x) = \exp\left(\frac{2s^T x - s^T s}{2\sigma^2}\right) = \underset{D_0}{\overset{D_1}{\gtrless}} \gamma \tag{16}$$

By applying logarithm on both sides

$$L(x) = \ln(\lambda(x)) = \left(\frac{2s^T x - s^T s}{2\sigma^2}\right) = \underset{D_0}{\overset{D_1}{\gtrless}} \ln(\gamma)$$

Where L(x) is called log-likelihood ratio (LLR).

$$T(x) = s^T x \underset{D_0}{\overset{D_1}{\gtrless}} \sigma^2 \ln(\gamma) + \frac{1}{2} s^T s = \gamma' \tag{17}$$

Choose γ', to maximize P_D and satisfy the false alarm rate constant.

$$P_{FA} = \int_{\gamma}^{\infty} f(x/H_0)dx = \alpha \tag{18}$$

The mean value of T(x) is

$$E\{T(x)/H_0\} = E\{w^T s\} = E\{w^T\}s = 0 \tag{19}$$

$$E\{T(x)/H_1\} = E\{(s+w)^T s\} = s^T s = \varepsilon \tag{20}$$

Variance of T(x) is

$$\begin{aligned} Var\{T(x)/H_i\} &= E\{(w^T s)^2\} \\ &= s^T E\{ww^T\}s = \sigma^2 s^T s \\ Var\{T(x)/H_i\} &= \sigma^2\varepsilon, i = 1,2 \end{aligned} \tag{21}$$

$$T(x) \sim \begin{cases} N(0,\sigma^2\varepsilon), & for\, H_0 \\ N(\varepsilon,\sigma^2\varepsilon), & for\, H_1 \end{cases}$$

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Let Let $T'(x)=\frac{T(x)}{\sqrt{\sigma^2\varepsilon}}$ (22)

Then

$$T'(x)\sim\begin{cases}N(0,1),\ for\ H_0\\ N(\sqrt{\varepsilon/\sigma^2},1),\quad for\ H_1\end{cases}$$

Threshold value can be calculated as

$$P_{FA}=p(T>\gamma'/H_0)=p\left(T'>\frac{\gamma'}{\sqrt{\sigma^2\varepsilon}}\Big/H_0\right)$$

Where $T'(x)=\frac{T(x)}{\sqrt{\sigma^2\varepsilon}}$

$$P_{FA}=Q\left(\frac{\gamma'}{\sqrt{\sigma^2\varepsilon}}\right)$$

$$\frac{\gamma'}{\sqrt{\sigma^2\varepsilon}}=Q^{-1}(P_{FA})$$

$$Threshold\ value=\gamma'=\sqrt{\sigma^2\varepsilon}\,Q^{-1}(P_{FA}) \quad (23)$$

Probability of detection(P_D) can be obtained as

$$P_D=p(T>\gamma'/H_1),\quad T\sim N(\varepsilon,\sigma^2\varepsilon)$$

and $\gamma'=\sqrt{\sigma^2\varepsilon}\,Q^{-1}(P_{FA})$

$$P_D=Q\left(\frac{\gamma'-\varepsilon}{\sqrt{\sigma^2\varepsilon}}\right)$$

$$P_D=Q\left(\frac{\sqrt{\sigma^2\varepsilon}\ Q^{-1}(P_{FA})-\varepsilon}{\sqrt{\sigma^2\varepsilon}}\right)$$

Thus

$$P_D=Q\left(Q^{-1}(P_{FA})-\sqrt{\frac{\varepsilon}{\sigma^2}}\right) \quad (24)$$

IV. Results

In this paper, a matched filter-based spectrum sensing technique has been used to sense the spectrum holes consistently and resourcefully for cognitive radio networks.

We obtained various threshold values of a matched filter according to the condition of Log-Likelihood Ratio test as well as Neyman-Pearson observer. We observed that at low SNR values, sometimes the noise power is greater than the threshold value of the matched filter technique using LLR test. It may give wrong decisions. In such cases, if we use NP criteria, it will give better result compared with the LLR test. Table 1 gives comparison between threshold values of LLR test and NP observer.

We also obtained the ROC curve at SNR value 0.5dB, which is shown in fig. 3.

Neyman Pearson threshold range plot is Shown in Fig. 4. The plot is taken for 1e5 Monte Carlo trials.

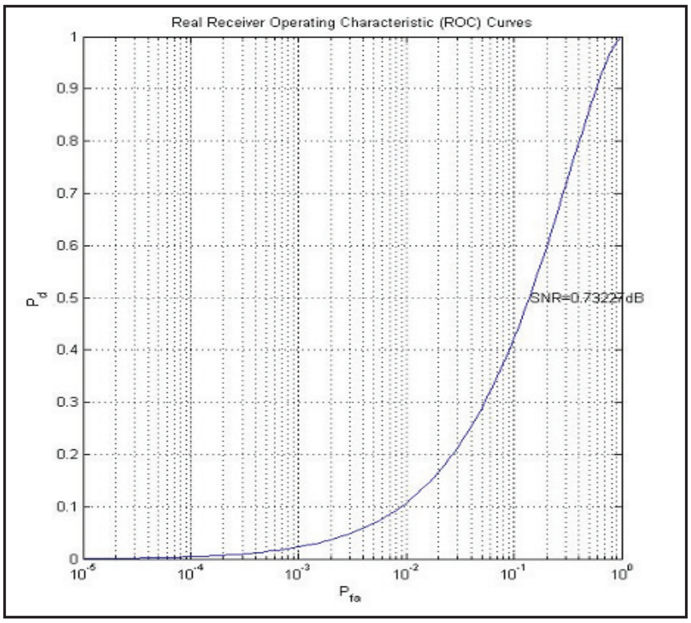

Fig. 3: ROC curve at SNR=0.5db

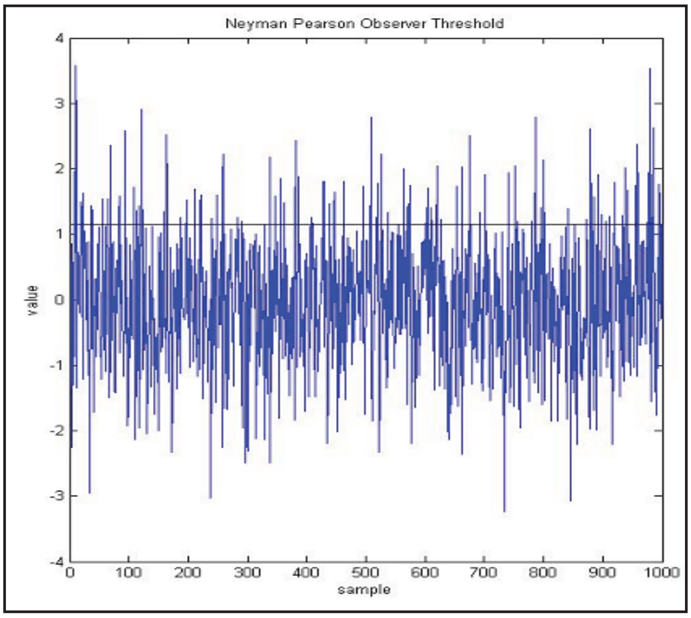

Fig. 4: Neyman Pearson Observer Threshold at SNR=0.5db

Table 1: Statistics of Threshold values of Different SNR ranges

S.No.	Input Power(db) X(t)	Likelihood Ratio Threshold (db)	Neyman Pearson Threshold (db)	Pd (db)
1	0.5	1.6197	1.1479	0.7323
2	1	1.5291	1.0997	0.7016
3	1.5	1.4435	1.0548	0.6713
4	2	1.3628	1.0130	0.6416
5	3	1.2146	0.9377	0.5850
6	5	0.9648	0.8157	0.4860
7	7	0.7664	0.7236	0.4076
8	9	0.6087	0.6538	0.3478
9	10	0.5482	0.6254	0.3237
10	15	0.3051	0.5283	0.2436
11	20	0.1716	0.4773	0.2037
12	25	0.0965	0.4497	0.1831

V. Conclusion

The advantage of the proposed schemes comes from the fact that it can work with very low SNR values. All it needs is only the prior knowledge of the PU signal, the prior probability of the PU activity and SNRs of the PU signal at Cognitive Radio Terminals. Monte-Carlo simulation results based on ROC curve shows that the sensing performance of the proposed scheme gives better performance. We observed that an improvement of accuracy in detection and an increase in the reliability of detection by using Neyman Pearson Observer. It implies good detection results at both low and high SNR. The method has good accuracy at Low SNR values without any loss in Pfa. The wrong decisions observed above 20db can be controlled by NP Observer. Hence using this method accuracy and reliability on decision is good.

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