

Cognitive Radio with Fast Sensing Technique Using Autocorrelation Approach

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Abstract — The dynamic spectrum allocation is important to improve spectrum efficiency usage of available radio spectrum. Cognitive radio has emerged as a solution to dynamic spectrum access, due to its adaptability and re-configurability. The main problem of cognitive radio is how the secondary users can detect the holes in the frequency band of the primary users. Spectrum sensing is the main feature of cognitive radio technology. Finding a more accurate and efficient spectrum sensing technique is the core of cognitive radio technology to develop dynamic resource management in future wireless networks. A spectrum sensing based on the auto correlation technique provides performance improvement at very low SNR over the energy detection technique. In this paper, we show the autocorrelation spectrum sensing features over energy detection spectrum sensing technique. Analytical and Simulation results are performed in a non-fading and a fading environment as well. The results show that the autocorrelation technique has enormous superiority in performance over that of the energy technique.

Keywords — Cognitive radio, Spectrum sensing, Energy detection, Autocorrelation.

I. INTRODUCTION

Cognitive Radio (CR) permits the possibility of spectrum reuse [1, 2] where it allows static user which are called primary users (PU) and new users which are called secondary users (SU) share the spectrum dynamically [3, 4]. In a CR network the secondary users are allowed to utilize the frequency bands of primary users when these bands are not being utilized by the primary [5]. It enables the secondary users called CR users to use the spectrum along with primary users (PU) at a time when it is not used by incumbent radio systems [6]. Spectrum sensing is a main function for detecting the presence of primary signals [7]. The CR

users can be able to access the required spectrum only when CR users do not cause interference to the primary users. Consequently, continuous spectrum sensing is an important task in cognitive radio technology in order to know the presence of primary users continuously and accurately, so CRs must be more sensitive than PUs and efficient at lower SNR to detect PUs signals. Energy detection [8] is the simplest detection method but needs the exact knowledge of the noise level N_0 , furthermore, a wrong estimation is known to seriously impact the detection performance. The limitations of the energy detector performance are due to the presence of noise uncertainty and background interference. Among different methods of spectrum sensing in CR is the cyclostationary detection [7] method which is also known as spectral correlation method because it uses cyclic correlation function for detecting the presence of signal in a given spectrum. The cyclic features of communication signals are exploited using spectral correlation analysis as a method for spectrum sensing. The major advantage of this scheme is its ability to differentiate between noise and modulated signals [9]. This is possible because unlike communication signals, noise is a stationary process with no correlation and does not give rise to cyclic features. As a result, cyclic feature detection is robust to noise and interference uncertainty problems. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation or they can be intentionally induced to assist spectrum sensing. In this paper, we analyze and simulate the autocorrelation technique in a non-fading and fading channel and compare the results with the performance of energy sensing technique [11, 12]. This paper is organized as follows: section II introduces the signal model and describes the autocorrelation approach

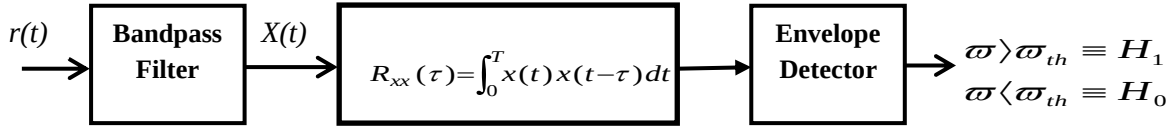


Fig.1 Block Diagram of Auto-correlation Method

used for spectrum sensing. Section III gives the numerical and simulation results. Finally, section IV gives the conclusion.

II. SIGNAL MODEL AND DETECTION

A simple auto-correlation method is shown in Fig.1, where $x(t) = s(t) + n(t)$ is a band-limited received signal of duration T and carrier frequency f_c , where $s(t)$ is the transmitted signal and $n(t)$ is the additive white Gaussian noise. Let us consider a finite received signal samples $x(n)$, $x(n-1)$, ..., $x(n-N+1)$ of length N , the correlated output of the received samples $x(n)$ can be written as

$$r_{xx}(l) = \frac{1}{N} \sum_{n=0}^{N-1} x(n)x(n-l), \quad l > 0 \quad (1)$$

The elements of $r_{xx}(l)$ form a sample correlation matrix r_{xx} with a dimension of $M \times M$ where M is the maximum value of $lag(l)$ [10], and the corresponding noise correlation matrix is r_{ww} . The autocorrelation function of a bandpass noise is a modulated sinc function whose envelope has its first zero crossing at $1/W$, where W is the bandwidth of the noise. However the envelope of the autocorrelation function of the signal will deviate a sinc depending on the transmit symbol rate, modulation and pulse shaping. When correlation is present in this signal, the first zero crossing of the autocorrelation will happen at larger time lag than that of the noise. The bandpass noise can be represented as

$$n(t) = n_c(t) \cos(2\pi f_c t) - n_s(t) \sin(2\pi f_c t) \quad (2)$$

where $n_c(t)$ and $n_s(t)$ are the in-phase and quadrature modulation components, respectively. The autocorrelation function of the noise component $n_c(t)$ over duration T is defined as

$$R_c(\tau) = \int_0^{T-\tau} n_c(t)n_c(t+\tau)dt \quad (3)$$

In discrete time this is approximately can be written as

$$R_{ck} \approx \frac{1}{W} \sum_{i=1}^{TW-k} a_{ci} a_{c(i+k)} \quad (4)$$

where k is the lag in samples which satisfies $k = W\tau$. where a_{ci} is the i th sample (taken at an interval of $1/W$) of $n_c(t)$. The results are same for $n_s(t)$ by replacing 'c' with 's' in (3), (4) we can obtain R_{sk} . Since $n_c(t)$ and $n_s(t)$ are sampled at the rate of W samples/s, the samples are uncorrelated. The discrete envelope of the autocorrelation function of the bandpass noise can be represented as

$$\begin{aligned} \hat{R}_k &= \frac{1}{2} [R_{ck} + R_{sk}] \\ &= \frac{1}{2W} \sum_{i=1}^{TW-k} [a_{ci} a_{s(i+k)} + a_{si} a_{c(i+k)}] \end{aligned} \quad (5)$$

The CorrSum method [13] exploits the autocorrelation at the time lag of $\tau = 1/W$ corresponding to $k = 1$ which is done by integrating the envelope of the autocorrelation of the received signal to the first null of the autocorrelation of bandpass noise, or

$$\Xi = \int_0^{1/W} \hat{R}(\tau) d\tau \approx \frac{1}{2W} [\hat{R}_0 + \hat{R}_1] \quad (6)$$

From (5) and (6), and simplification analogous to (2), we get

$$\hat{R}_0' = N_0 \sum_{i=1}^{TW} [b_{ci}^2 + b_{si}^2] \quad (7)$$

And

$$\hat{R}_1' = N_0 \sum_{i=1}^{TW-1} [b_{ci} b_{c(i+1)} + b_{si} b_{s(i+1)}] \quad (8)$$

where b_{ci} , b_{si} , $b_{c(i+1)}$ and $b_{s(i+1)}$ are all zero mean Gaussian random variables with unit variance. Let us consider the decision statistic $\varpi = 2W(\Xi / N_0)$, then from (6) ϖ can be written as

$$\begin{aligned} \varpi &= \frac{2W}{N_0} \int_0^{1/W} \hat{R}(\tau) d\tau \\ &= \hat{R}_0' + \hat{R}_1' \end{aligned} \quad (9)$$

The distribution of $\hat{R}_1'$ in previous equations is difficult to calculate in closed form. However, when $2(TW - 1)$ is sufficiently large, the distribution is well approximated as

Gaussian, requiring only mean and variance of the decision statistic. In the case of noise only, we have

$$E[\hat{R}_0] = 2TW, \text{ and } E[\hat{R}_1] = 0 \quad (10)$$

So, under hypothesis H_0 , the main and the variance of the decision statistic are given as

$$E[\varpi] = E[\hat{R}_0'] + E[\hat{R}_1'] = 2TW \quad (11)$$

$$\begin{aligned} \text{var}[\varpi] &= \text{var}[\hat{R}_0' + \hat{R}_1'] \\ &= \text{var}[\hat{R}_0'] + \text{var}[\hat{R}_1'] + 2\text{cov}[\hat{R}_0', \hat{R}_1'] \\ &= 4TW + 2(TW - 1) \end{aligned} \quad (12)$$

where $\text{Var}[\hat{R}_0'] = 4TW$, $\text{Var}[\hat{R}_1'] = 2(TW - 1)$, and the covariance between $\hat{R}_0'$ and $\hat{R}_1'$ is found to be zero. In the case when the signal is present, the bandpass signal $x(t)$ can be represented in a similar form as the noise as

$$x(t) = x_c(t) \cos(2\pi f_c t) - x_s(t) \sin(2\pi f_c t) \quad (13)$$

the envelope of the autocorrelation function of the received signal is integrated up to its first null $\tau = 1/W$ and this value is used as a decision statistic to test the hypothesis H_1 that a primary user is present, which exploits both the energy and autocorrelation of the received samples. The in-phase and quadrature component of $x(t)$ have variances equal the signal power. The i th sample of $x_c(t)$ and $x_s(t)$ have an average power equal to the signal-to-power ratio γ . The derivation of the main and the variances of the decision statistic ϖ using the CorrSum method are listed in [7, 13] for hypothesis H_1 and those values are given as

$$E(\varpi) = 2TW(1 + \gamma) + 2(TW - 1)\rho_1\gamma \quad (14)$$

where ρ_1 is the autocorrelation coefficient of the signal for a lag of one sample.

$$\text{Var}(\varpi) = \text{Var}(\hat{R}_0') + \text{Var}(\hat{R}_1') + \text{Cov}_{cc}. \quad (15)$$

Where each component of (14) is defined as

$$\text{Var}(\hat{R}_0') = 4TW(1 + 2\gamma) \quad (16)$$

And

$$\begin{aligned} \text{Var}(\hat{R}_1') &= 2(TW - 1)[1 + 2\gamma + (1 + \rho_1^2)\gamma^2] \\ &+ 4 \sum_{j=1}^{TW-2} (TW - 1 - j) \text{Cov}_j. \end{aligned} \quad (17)$$

where the covariance's are given as

$$\text{Cov}_1 = (\rho_2 + \rho_1^2)\gamma^2 + \rho_2\gamma \quad (18)$$

$$\text{Cov}_j = (\rho_{j-1}\rho_{j+1} + \rho_1^2)\gamma^2, \quad 2 \leq j \leq TW - 2 \quad (19)$$

the autocorrelation coefficient ρ_j for a lag of j samples is given as

$$\begin{aligned} \rho_j &= \frac{1 + j\eta}{\pi} \text{si}\left\{\left(\frac{1}{\eta} + j\right)\pi\right\} + \frac{1 - j\eta}{\pi} \text{si}\left\{\left(\frac{1}{\eta} - j\right)\pi\right\} \\ &- \frac{2j\eta}{\pi} \text{si}(\pi j) + \frac{\eta}{\pi^2} (\cos\{\left(\frac{1}{\eta} - j\right)\pi\} + \\ &\cos\{\left(\frac{1}{\eta} + j\right)\pi\}) - \frac{2j\eta}{\pi} \end{aligned} \quad (20)$$

where $\eta = R_s/W$ is the ratio of the primary transmission symbol rate R_s and sensing bandwidth W , and $\text{Si}(\cdot)$ is the sine integral defined as

$$\text{si}(u) = \int_0^u \frac{\sin x}{x} dx. \quad (21)$$

The Cov_{cc} is the correction component due to the covariance between $\hat{R}_0'$ and $\hat{R}_1'$ and is given as

$$\begin{aligned} \text{Cov}_{cc} &= 8(2TW - 3)\rho_1\gamma^2 + 8(2TW - 3)\rho_1\gamma + \\ &= 2 \sum_{j=1}^{TW-2} [4(2TW - 3) - 8j]\rho_j\rho_{j+1}\gamma^2 \end{aligned} \quad (22)$$

For the CorrSum method, the probability of a false-alarm P_f under hypothesis H_0 can be calculated as [13]

$$P_f = \Pr(\varpi > \varpi_{th} | H_0) = \frac{1}{2} \text{erfc}\left[\frac{\varpi_{th} - \mu_n}{\sqrt{2}\sigma_n}\right] \quad (23)$$

where ϖ_{th} is the decision threshold and from (11), (12) we can find $\mu_n = 2TW$ and $\sigma_n^2 = 4TW + 2(TW - 1)$. The probability of detection under hypothesis H_1 is given as

$$P_d = \Pr(\varpi > \varpi_{th} | H_1) = \frac{1}{2} \text{erfc}\left[\frac{\varpi_{th} - \mu_{sn}}{\sqrt{2}\sigma_{sn}}\right] \quad (24)$$

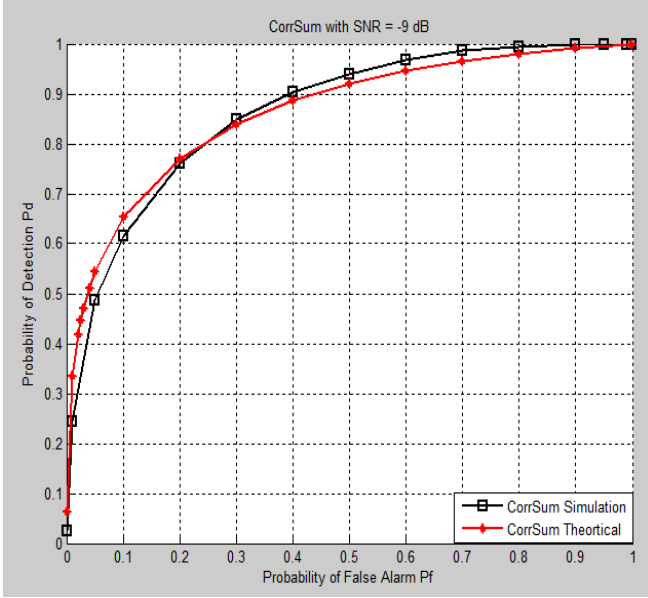


Fig.2 Probability of detection (P_d) vs. Probability of false alarm (P_f) with signal to noise ratio (SNR=-9dB).

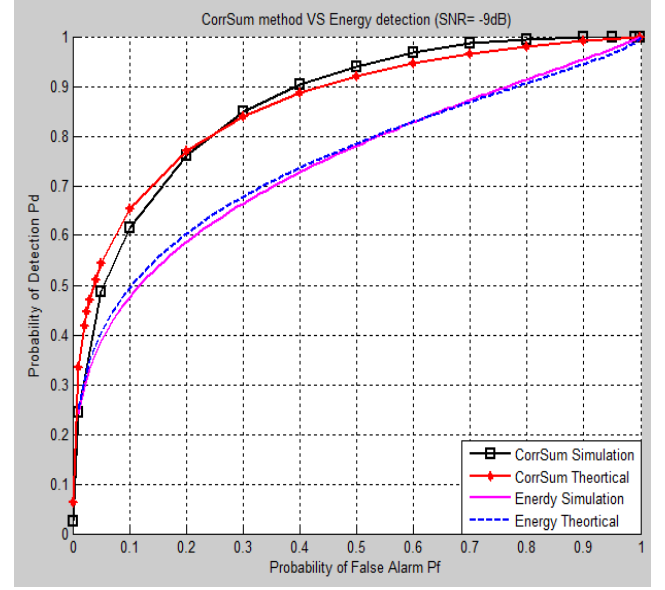


Fig.3 P_d against P_f for energy detection and Corrsum method at SNR=-9 dB.

Where from (13), (14) we can find the values of

$$\mu_{sn} = 2TW(1 + \gamma) + 2(TW - 1)\rho_1\gamma$$

and

$$\sigma_{sn}^2 = 4TW(1 + 2\gamma) + (2TW - 2)[1 + 2\gamma + (\rho_1^2 + 1)\gamma^2] + 8\rho_1\gamma(2TW - 3) + 8\rho_1\gamma^2(2TW - 3) + 4 \sum_{i=1}^{TW-2} ((TW - 1 - j)Cov_j + (4TW - 4j - 6)\rho_j\rho_{j+1}\gamma^2)$$

III. Numerical and Simulation Results

The performance of the system model based on CorrSum method is performed according to analytical expressions and Monte Carlo simulations at different symbol rates and modulations techniques. The results of the CorrSum are considered with a symbol rate of 10 MS/s and sensing bandwidth of 20 MHz ($\eta = 0.05$), the maximum symbol rate that can effectively be transmitted ($2TW = 160$). In Fig.2, we observe that the simulation result coincide with theoretical result with very small difference. The theoretical and simulation performance for energy detection method [11, 12] are shown in Fig.3. Where, we show the performance of CorrSum method has high performance than the Energy detection method for all values of false alarm probability greater than 0.05 at SNR = -9 dB. In Fig.4 the probability of detection are evaluated at different values of SNR for the CorrSum method and the Energy detection using the simulation and theoretical analysis, we find that there are cross-section between the two method at SNR= -9.345 dB and the CorrSum has high performance above this value. The probability of

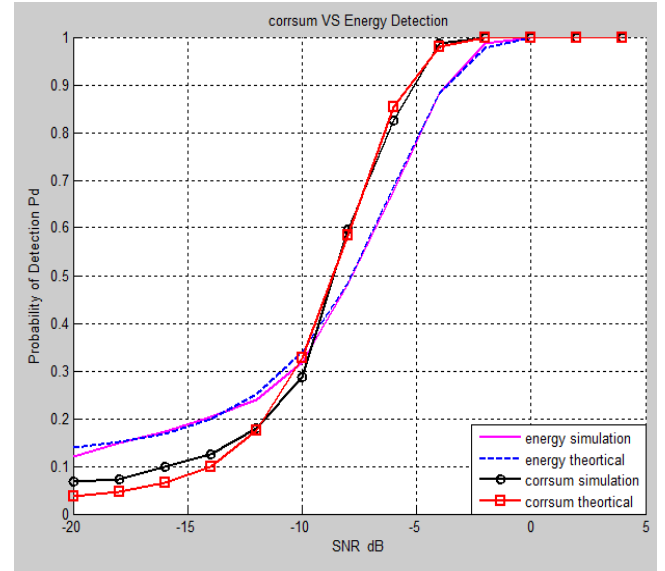


Fig.4 P_d versus SNR for energy detection and CorrSum method at $P_f = 0.05$.

detection is calculated based on the different probability of false alarm and different time bandwidth factors (L) in Fig.5. The results in Fig.5 are calculated at values of time bandwidth product $L = 1000$ & 2000 for the two method, it can be notice that the CorrSum method exhibits better probability of detection for the two values of L when probability of false alarm greater than 0.1 As shown in Fig.6 the probability of detection for the CorrSum method has high immunity in fading environment than the energy detection method when probability of false alarm is greater than 0.1

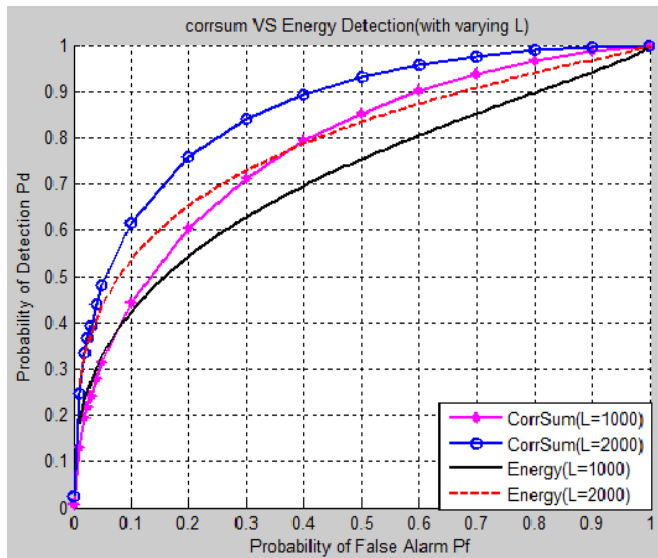


Fig.5 P_d v.s P_f in energy detection and CorrSum at different values of time bandwidth factor (L).

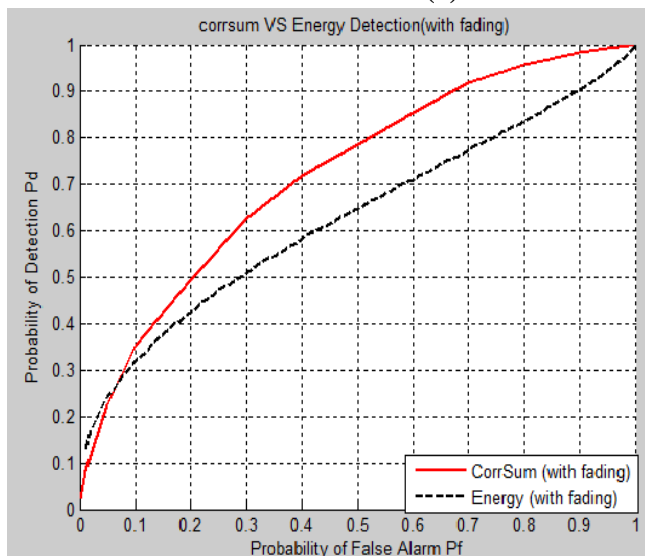


Fig.6 P_d versus P_f in Rayleigh fading environment.

IV. CONCLUSIONS

In this paper, the theoretical and simulation analysis of the autocorrelation spectrum sensing technique are performed and compared with energy detection technique at different values of SNR and at different values of time band width product factor. The results show that the autocorrelation approach has better performance than the energy detection and high immunity against the fading environment. It can be concluded that the autocorrelation feature detector is the best sensing detection technique for cognitive radio technology.

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