# A NOVEL CORRELATION SUM METHOD FOR COGNITIVE RADIO SPECTRUM SENSING

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## I. INTRODUCTION

Cognitive radio is a promising concept for coping with the spectrum scarcity in future generation wireless communication networks. This idea, including software-defined radio (SDR) as the enabling technology, was suggested by Mitola [1] to realize flexible and efficient usage of spectrum. An important component of cognitive radio is spectrum sensing to detect the presence or absence of a primary (licensed) user in the spectrum for a given location. Some existing spectrum sensing techniques found in the cognitive radio literature are matched filtering, waveform-based sensing [2], cyclostationary-based sensing [3], [4], energy detection [5]-[8], and radio identification. In this paper we present a new correlation sum method, and compare its performance with energy detection, which is the most common way to detect the presence of generalized, unknown signals.

The rest of the paper is organized as follows: Section II introduces the problem of spectrum sensing and discusses energy-based detection. Section III describes our correlation sum method for sensing. Section IV gives some simulation results with discussions. Conclusion and future extensions are discussed in Section V.

## II. SPECTRUM SENSING FOR COGNITIVE RADIO

Spectrum sensing determines the presence or absence of the primary user based on a specific detection model. In this work, we assume a received signal with the simple form $y\left(n\right) = s\left(n\right) + w\left(n\right)$, where $s\left(n\right)$ is the signal to be detected, $w\left(n\right)$ is an additive white Gaussian noise (AWGN) sample, and $n$ is the sample index. Note that when no primary user is transmitting, $s\left(n\right) = 0$.

### *1) Energy-Detector Sensing*

Energy detection is taken as the reference for comparison in this paper, since it is general and can be applied to any unknown signal [5]. The method has also been analyzed in the presence of signals with random amplitude and channel fading [6],[7]. For a lowpass signal having bandwidth $W$, the energy in a sample record of duration $T$ is approximated by $2TW$, where the received waveform is sampled at the rate $2W$. The energy is expressed as

$$E = \int_0^T n^2\left(t\right)\,dt \approx \left(\frac{1}{2W}\right)\sum_{i=1}^{2TW} a_i^2 \tag{1}$$

where $n(t)$ is a Gaussian noise process, and $a_i$ is the $i$th noise sample.

The results are the same for a bandpass processes provided that $W$ is interpreted as the positive frequency bandwidth. For zero mean Gaussian distributed noise only ($\mathsf{H}_0$), the energy $E$ follows central chi-square $\left(\chi^2\right)$ distribution with $2TW$ degrees of freedom. In the case that the primary user (signal) is present ($\mathsf{H}_1$), $E$ follows a non-central chi-square $\left(\chi^2\right)$ distribution with $2TW$ degrees freedom and a non-centrality parameter $2\gamma$, where $\gamma$ is the signal-to-noise ratio (SNR), or

$$E = \begin{cases} \chi^2_{2TW} & \mathsf{H}_0, \\ \chi^2_{2TW}\left(2\gamma\right) & \mathsf{H}_1, \end{cases} \tag{2}$$

where the sensing time $T$ is chosen such that $2TW$ is an integer. The block diagram of energy detection is shown in Fig. 1.

The probability of false alarm $P_F$ and the probability of correct detection $P_D$ are calculated as [7]

$$P_f = Pr\left(Y > \lambda|\mathsf{H}_0\right) = \frac{\Gamma\left(u, \frac{\lambda}{2}\right)}{\Gamma\left(u\right)} \quad \text{and} \quad P_d = Pr\left(Y > \lambda|\mathsf{H}_1\right) = Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda}\right), \tag{3}$$

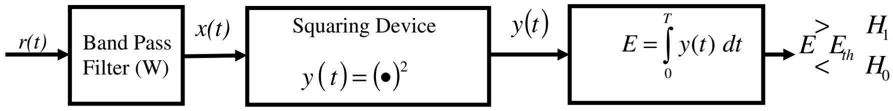


Fig. 1. Block diagram of an energy detector

where $\lambda$ is the decision threshold, $\Gamma(.,.)$ is the incomplete gamma function, and $u = TW$ is the time bandwidth product. As expected, $P_f$ is independent of $\gamma$ since under $\mathsf{H}_0$ there is no primary signal present.

## III. Proposed Correlation Sum Method

Instead of only considering the energy of the signal to be detected, we can exploit any properties that exist in signal that are not present in the noise. One such property is the autocorrelation of the samples. The autocorrelation function of 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 (as well as the sensing bandwidth). However, the envelope of the autocorrelation function of the signal will deviate from 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 a larger time lag than that of the noise.

To detect the deviation of the received waveform from noise, the envelope of the empirical 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 that a primary user is present, which exploits both the energy and autocorrelation of the received samples. A block diagram of the correlation sum method is shown in Fig. 2.

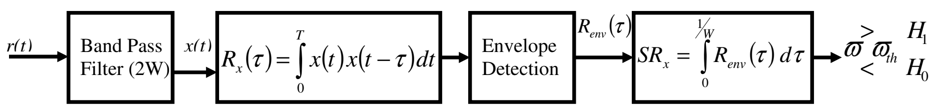


Fig. 2. Block diagram of the correlation sum method

The autocorrelation and power spectral density (PSD) of ideal lowpass noise are related by the the Fourier transform pair [9]

$$\operatorname{sinc}(W\tau) \longleftrightarrow \frac{1}{W} \operatorname{rect}\left(\frac{f}{W}\right), \tag{4}$$

where $W/2$ is the bandwidth of the lowpass signal. The bandpass signal for a center frequency of $f_c$ is obtained by shifting the spectrum to $+f_c$ and $-f_c$, resulting in bandwidth $W$. From the frequency shifting property [9], the PSD is related to the autocorrelation as

$$A \operatorname{sinc}(W\tau)\cos 2\pi f_c \tau \longleftrightarrow \frac{A}{2W}\left[\operatorname{rect}\left(\frac{f-f_c}{W}\right) + \operatorname{rect}\left(\frac{f+f_c}{W}\right)\right]. \tag{5}$$

The left hand side of (5) is the autocorrelation function of the bandpass noise. Its theoretical plot is shown on the left hand side of the Fig. 3. For later convenience, $A$ is taken to be $1.6 \times 10^5$ to compare it with the simulated autocorrelation with the same energy. The x-axis is time lag $(\tau)$ multiplied by the sampling rate $F_R$ to obtain integer values. The envelope of the autocorrelation is $A \operatorname{sinc}(W\tau)$, which is plotted on the right-hand side of Fig. 3, showing that the first null of the envelope of the autocorrelation appears at $\tau = 1/W$, corresponding to 40 samples on the $\tau F_R$ axis.

An example of the autocorrelation and single-sided PSD of simulated bandpass noise taking $1.6 \times 10^5$ samples with unit variance is shown in Fig. 4. Similarly, the autocorrelation and PSD of a QPSK signal with symbol rate 1 MS/s is shown in Fig. 5, indicating a more gradual decay of the autocorrelation function compared to the noise. Note that the integration of the envelope from $\tau = 0$ to $\tau = 1/W$ is significantly larger than that of the noise, even when the energies are equal.

## IV. Performance Comparison

### A. Noise Only (No Fading)

Simulations of the correlation sum method were carried out for a BPSK signal (rectangular pulses) with a symbol rate of either 1 MS/s and 10 MS/s and a sensing bandwidth of 20 MHz. These simulations are compared to energy

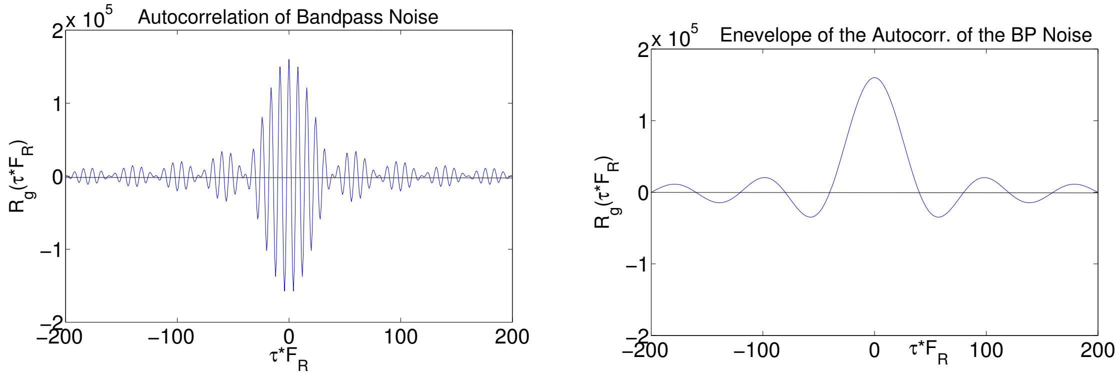


Fig. 3. Theoretical autocorrelation function and its envelope for bandpass noise for a bandwidth of 20 MHz and sample rate $800 \times 10^6$ Samples/s.

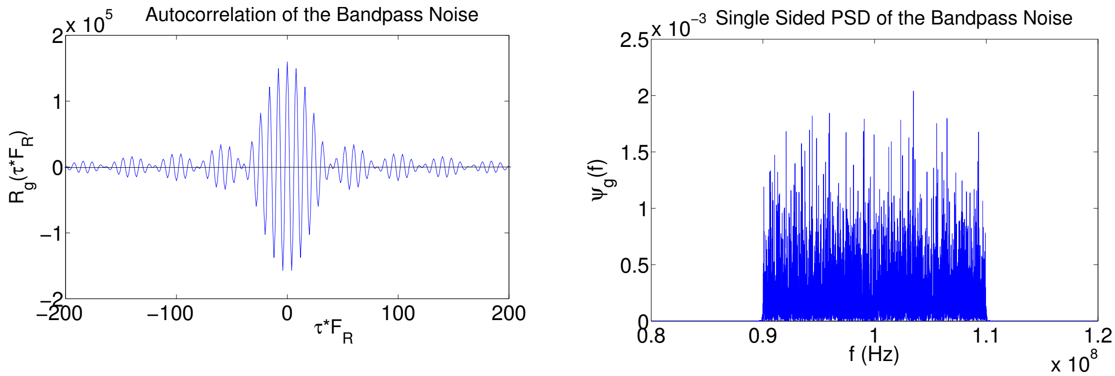


Fig. 4. The Autocorrelation and PSD (Single-Sided) of the Bandpass Noise of Bandwidth $20MHz$

detection for a sensing time of 0.002 ms ($2TW = 40$), and the results are shown in Fig. 6. The improvement in the probability of detection offered by the correlation sum method is readily apparent.

The results in Fig. 6 indicate that although the performance of energy detection does not depend on the symbol rate, the performance of the correlation sum method is degraded with increasing symbol rate. In the limit as the symbol rate becomes large, the transmission bandwidth is also large and the spectrum inside the sensing window becomes flat and similar to noise. In this case, the performance of the correlation sum method approaches that of the energy detector.

The simulation was also carried out for a QPSK signal with the same parameters used for BPSK, but the performance is basically identical. The reason is that for the same symbol rate, the spectrum of BPSK and QPSK signals are similar.

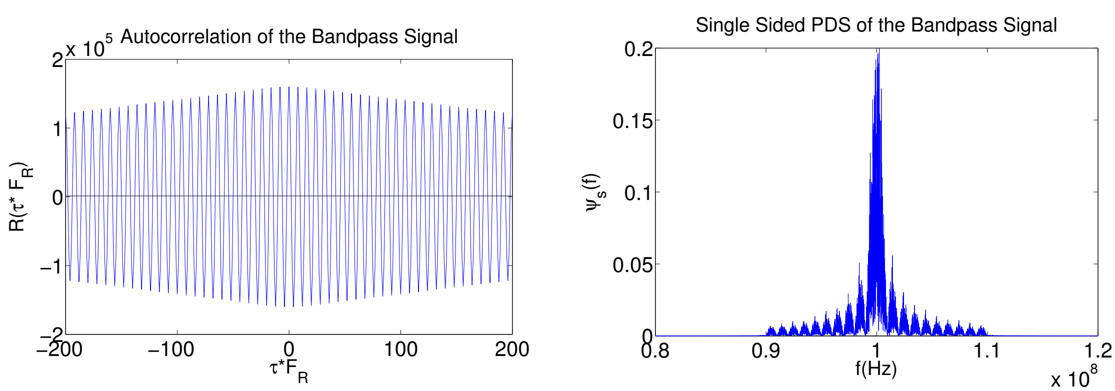


Fig. 5. The autocorrelation and PSD (Single-Sided) of the bandpass QPSK Signal (1 MS/s) with a filter bandwidth of 20 MHz

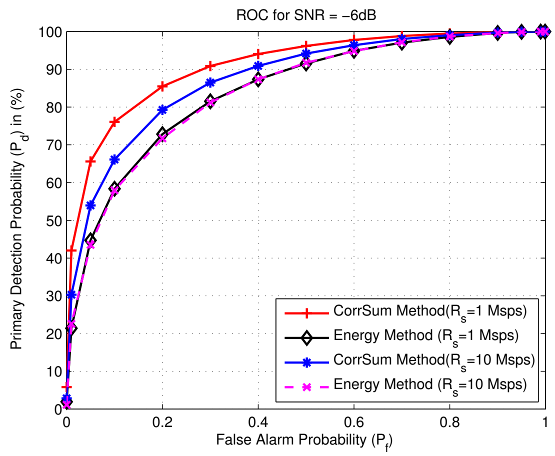


Fig. 6. ROC curves comparing the performance of the correlation sum method and energy detection method for different symbol rates assuming BPSK transmission

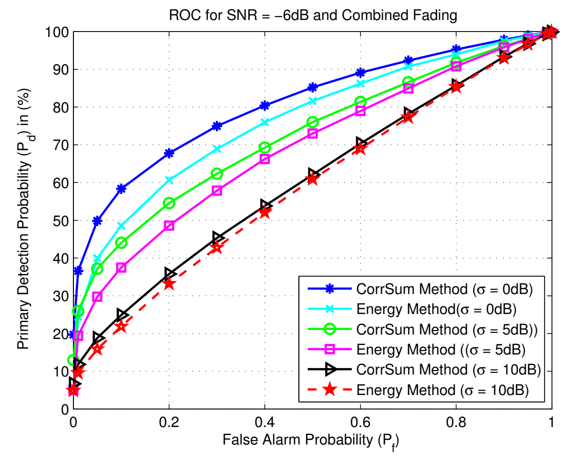


Fig. 7. ROC curves comparing the performance of the correlation sum method and energy detection method in different levels of shadowing

### B. Performance in Fading Environments

In practice, the sensing problem involves both small-scale (multipath) and large-scale (shadow) fading. These two effects are commonly treated as independent processes that combine to produce the overall fading effect [10], and this effect usually degrades existing spectrum sensing methods. The performance of the correlation sum and energy detection methods in a fading environment with three different levels of log-normal shadowing is shown in Fig. 7, where $\sigma$ is the log-normal shadowing standard deviation. It can be seen that for severe combined fading $P_d$ approaches $P_f$, indicating that the presence of the user cannot be detected. However, the performance of the correlation sum method is better than energy detection in all fading cases. Due to space limitations, detailed information on the fading simulations is saved for the presentation.

## V. Conclusion

Efficient sensing of the available spectrum opportunities is an important element of cognitive radio. This work proposed a new correlation sum method and its performance was compared with standard energy detection. Simulation results indicate that the new correlation sum method has better performance than energy detection for different types of modulation in both static and fading environments. In future work, we plan to investigate the performance of the new method for collaborative sensing, multiple antennas per user, and more realistic channel models.

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