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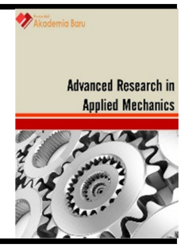


# Spectrum Sensing by Scattering Operators in Cognitive Radio

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A. Moawad[1,2,*], K. C. Yao[2], A. Mansour[3], R. Gautier[2]

[1] Department of Electronics & Communications Engineering, AAST, Cairo, Egypt
[2] LABSTICC, UBO, 29238 Brest, France
[3] LABSTICC, ENSTA Bretagne, 29806 Brest, France

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**ABSTRACT**

The detection of signal presence is a crucial job carried out through spectrum sensing in cognitive radio systems. A tradeoff between detection accuracy and detector complexity is tackled often in researches. Amongst different spectrum sensing techniques, conventional energy detection is widely used due to its simplicity of implementation, however, it is sensitivity to noise variation makes it unreliable in low signal-to-noise-ratio environments. This manuscript proposes the use of scattering-based detector for spectrum sensing in the context of cognitive radio to provide reliable signal detection. Through scattering transform, signal features are enhanced whereas noise variations effects are reduced which enhances the detection results. The proposed detector is tested for chirp and spread spectrum signals in additive white Gaussian noise channel. Performance evaluation is conducted through calculation of detection probability for several signal-to-noise ratio values. Through MonteCarlo simulations, the proposed detector proves reliability of detection as compared to energy detection which provides false detection decision when noise only considered for detection.

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## 1. Introduction

The basic principles of cognitive radio (CR) technology define a wireless communication system as an intelligent system that employ understanding-by-building methodology to communicate with the surroundings [1]. Through this methodology, such system is able to learn from the environment and also to correspond to statistical variations by adapting its internal states in real-time. In CR, spectrum sensing (SS) is a major task in the cognition cycle to facilitate the access of a primary user (PU) frequency band by a secondary user (SU) (i.e., cognitive radio user) while maintaining quality of service (QoS). Through SS, a CR system detects the spectrum holes, thus this process must be performed fast while providing high detection accuracy. Hence, trade-offs between sensing time and accuracy of signal detection are often questioned in literature [2].

* *Corresponding author.*
*E-mail address: azza.moawad@univ-brest.fr (A. Moawad)*

Spectrum sensing techniques can be classified into cooperative and noncooperative techniques. In the former, information from multiple CR users is incorporated for PU detection whereas for the latter, user detection is based on the received signal at the CR receiver. The noncooperative techniques include energy detection (ED), matched filter detection (MFD), and cyclostationary feature detection (CFD) [3]. Energy detectors are easy to implement but they are sensitive to noise and channel impairments as well as they provide unreliable results in low signal-to-noise ratio scenarios. The matched filter detectors are optimum for additive white Gaussian noise (AWGN) channel but they require prior information about the PU signal which practically cannot be provided. Further, fine detection accuracy can be attained through CFD but on the expenses of increased complexity. Although conventional energy detectors are easy to implement and they do not require PU information and channel state information (CSI), they suffer from performance degradation especially in low signal-to-noise ratio (SNR) scenarios [4]. Accordingly, other energy-detection based techniques are proposed for performance improvements [5,6].

On the other hand, scattering transform provides a method for hierarchal signal representation based on deep convolutional networks (ConvNets) [7,8]. Its multi-stage architecture analyses the signal of interest into its significant features through every stage. Our main objective is to take advantage of the sparsity provided through wavelet filtering, nonlinearity and pooling to detect the presence of a signal. Needless to say, due to this cascaded signal analysis the noise effect is reduced and the detection accuracy is improved. In order to mitigate the problem of unknown signal detection in AWGN, this work introduces a novel spectrum sensing technique based on scattering transform (ST) as opposed to conventional energy detection (CED) to provide reliable detection in low SNR environments.

## 2. Scattering Transform: A State-of-Art

In scattering transform, a signal of interest is analysed through cascaded operations of complex modulus wavelet decomposition followed by averaging [8]. This iterative procedure brings up significant signals features and average out sources of time variation. A scattering network recovers high frequency information lost due to averaging through cascaded wavelet filters and rectification with complex modulus. Theoretically, the wavelet transform of the signal $x(t)$ is a convolution with the scaling function $\phi(t)$, which is a low pass filter with a time support defined by $T$, as well as convolving $x(t)$ with the wavelet function $\psi_\lambda(t)$ which is a band pass filter. With $\lambda$ being the center frequency of the filter, a dilated mother wavelet is given by

$$\psi_\lambda(t) = \lambda\, \psi_\lambda(\lambda t) \tag{1}$$

Then the wavelet transform of $x(t)$ can be written as

$$Wx = (x \star \phi(t), x \star \psi_\lambda(t))_{t\in\mathbb{R},\lambda\in\Lambda} \tag{2}$$

where $\Lambda$ is the set of all scattering network paths .by applying the complex modulus, the phase of all wavelet coefficients is removed and hence (2) becomes

$$|W|x = (x \star \phi(t), |x \star \psi_\lambda(t)|)_{t\in\mathbb{R},\lambda\in\Lambda} \tag{3}$$

To explain the iterative operation through the network, first, at the root of the network, we calculate the low-frequencies variation in the signal which is given by:

$$S_0 x(t) = x \star \phi\,(t) \tag{4}$$

To recover high frequency information lost by averaging, we apply the wavelet transform modulus operator

$$U_1 x\,(t, \lambda_1) = \left| x \star \psi_{\lambda_1}(t) \right| \tag{5}$$

To regain stabilization, the operator is averaged out such that we obtain

$$S_1 x(t, \lambda_1) = U_1 x\,(t, \lambda_1) \star \phi\,(t) \tag{6}$$

The latter is called first order scattering coefficients. These are computed with wavelets $\psi_{\lambda_1}(t)$ having $Q_1$ as an octave frequency resolution. The scattering operator at first order is convolved with second wavelets $\psi_{\lambda_2}(t)$ and after averaging we get

$$S_2 x(t, \lambda_1, \lambda_2) = \left| U_1 x\,(t, \lambda_1) \star \psi_{\lambda_2}(t) \right| \star \phi\,(t) \tag{7}$$

accordingly, the processes of energy averaging by $\phi\,(t)$ and energy scattering by $\psi_\lambda(t)$ are being repeated iteratively until the energy reaches a threshold. Thus for any order $m \geq 1$, the iterated wavelet modulus is given by

$$U_m x\,(t, \lambda_1, \ldots \lambda_m) = \left| \left| \left| x \star \psi_{\lambda_1}(t) \right| \star \psi_{\lambda_2}(t) \right| \star \ldots \left| \star \psi_{\lambda_m}(t) \right| \right. \tag{8}$$

and the scattering coefficients at order $m$ is given as

$$S_m x(t, \lambda_1, \ldots \lambda_m) = U_m x\,(., \lambda_1, \ldots \lambda_m) \star \phi\,(t) \tag{9}$$

**3. Spectrum Sensing with Scattering Operators**

Sensing the spectrum can be viewed as a binary hypothesis testing such that when the primary user (PU) is active, the received signal at the secondary user (SU) receiver can be given by [5]

$$y(t) = s(t) + u(t) \quad , under\ H_1: \ \text{PU present} \tag{10}$$

and when noise only present the received signal becomes

$$y(t) = u(t) \quad , under\ H_0: \ \text{PU absent} \tag{11}$$

where $u(t)$ is the noise imposed at the receiver input, s(t) the primary user's signal received by the secondary user receiver. Although energy detectors are easy to implement, they cannot differentiate significant signals and noise presence [4]. The first order scattering coefficients measures the time variation of signal amplitude within frequency bands covered by wavelet filter banks [8]. As for the second order coefficients, co-occurrence coefficients are calculated revealing interferences of a signal two successive wavelets $\psi_{\lambda_1}(t)$ and $\psi_{\lambda_2}(t)$ for all scales and translates [8]. Genuinely, filtering with wavelets is a measure of correlation between the investigated signal and the wavelet function. So even with low power signals, filtering with appropriate wavelets enhances these correlations which leads to significant energy measurements and reduces the noise effect. The architecture of the proposed spectrum sensing technique is shown in Figure 1. The procedures for spectrum sensing using scattering signal representation can be summarized as follows:

1- The received signal is processed through scattering network for signal decomposition which enhances signal contribution and reduces noise effect.
2- The resultant scattering coefficients are used for energy measurements as a test statistic $T$ and compared with the detection threshold $\gamma$. To reduce noise contribution, first order scattering coefficients are only used for detection

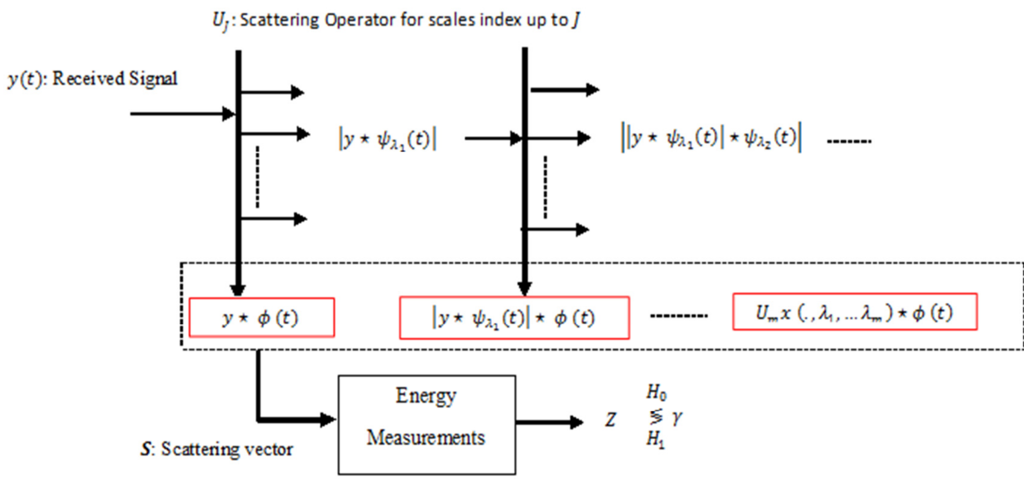


**Fig. 1.** Illustration of the received signal detection in the scattering domain

For testing purposes, the noise variance is assumed to be known which can be provided offline through experimental measurements. If the noise is additive white Gaussian noise (AWGN) with variance $\sigma_u^2$, the processed noise through complex modulus wavelet decomposition and averaging result in Rayleigh distributed process. Since the variance of a Rayleigh process $\sigma_r^2$ is defined by

$$\sigma_r^2 = \sigma_u^2(2 - \frac{\pi}{2}) \tag{12}$$

In this case the detection threshold is defined in terms of the variance of the scattered noise by:

$$\gamma = \sigma_u^2(2 - \frac{\pi}{2})||\psi_\lambda||^2 \tag{13}$$

## 4. Results and Discussion

In this section, we evaluate the performance of the time-scattering energy detector (TSED) as compared to conventional energy detector in low signal-to-noise ratio (SNR) scenario using first order scattering coefficients. This evaluation is conducted in additive white Gaussian noise (AWGN) channel. The primary user signal is being detected in for two types of communication signals, namely, Chirp Spread Spectrum (CSS) and BPSK-Direct Sequence Spread Spectrum (DSSS). The main objective is to evaluate the proposed energy detector in terms of detection probability and predetermined false alarm probability. The chirp signal is tested for 50 kHz sampling frequency and of duration of one second. The frequency variation starts at 1 Hz up to 2.5 kHz. The average

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window of the low pass filter of the scattering network is set to 2 msec. The sequence length is 50000 samples, and $10^6$ iterations is used for MonteCarlo simulation. As for the DSSS signal, the sequence length is 6400 samples. It is sampled at a rate of 1 kHz, with an average window of 32 msec. Figure 2 shows an example of the signal decomposition using scattering network for a noisy chirp signal. This visualization gives 3 sub-figures. The first one is the scalogram of the signal, the second is the averaged signal variation through first order scattering coefficients, and the third reveals the hidden signal variation due to noise by second order coefficients. Thus, these coefficients represent the noise contribution in the signal of interest and can be discarded for signal detection. This increases the reliability of the detector as compared to ED which measures the energy content of whatever present in a certain frequency band.

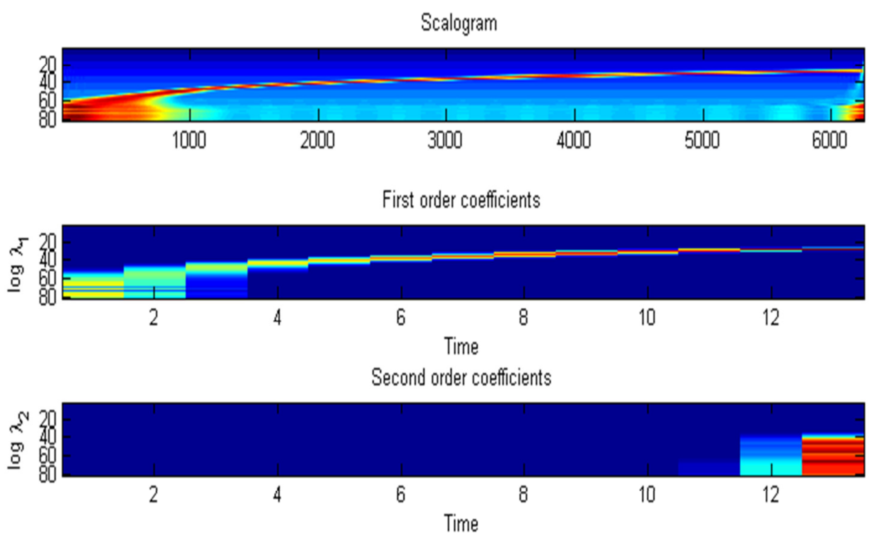


**Fig. 2.** Scattergram visualization of a chirp spread spectrum signal

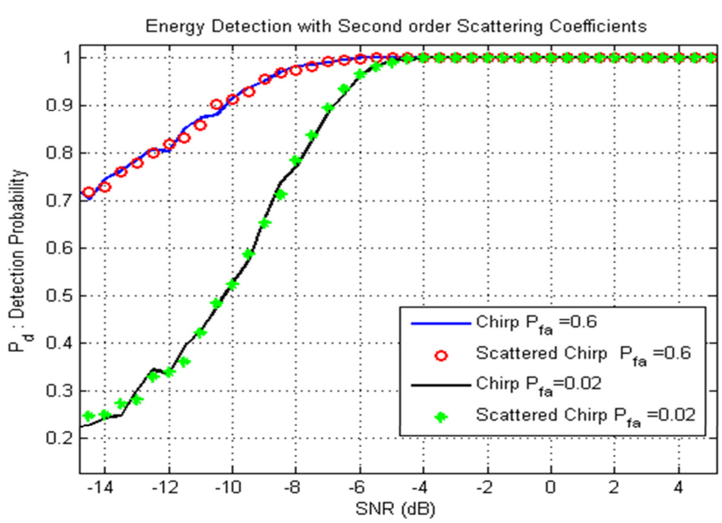


**Fig. 3.** Detection probabilities vs. SNR for a chirp spread spectrum signal

The detection probability is calculated for false alarm probabilities of 0.02 and 0.6 and shown in Figure 3 and Figure 4 for chirp and spread spectrum signals, respectively. These figures show that both detectors yields approximate performance. However, to test the reliability of the detectors, noise-only case is considered and false alarm probability is evaluated for different SNR. As observed in Figure 5, we notice that conventional ED declares a detection of a significant user at low SNR which is a false detection decision where the scattering based detector gives zero detection at low SNR up to -3dB when only first order coefficients are considered for detection. For noisy or interfered signals, these coefficients can reflect differences between original.

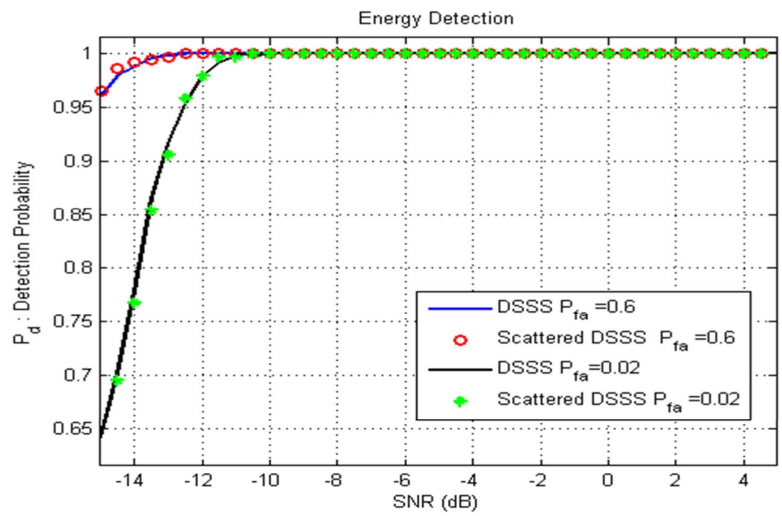


**Fig. 4.** Detection probabilities vs. SNR for direct sequence spread spectrum signal

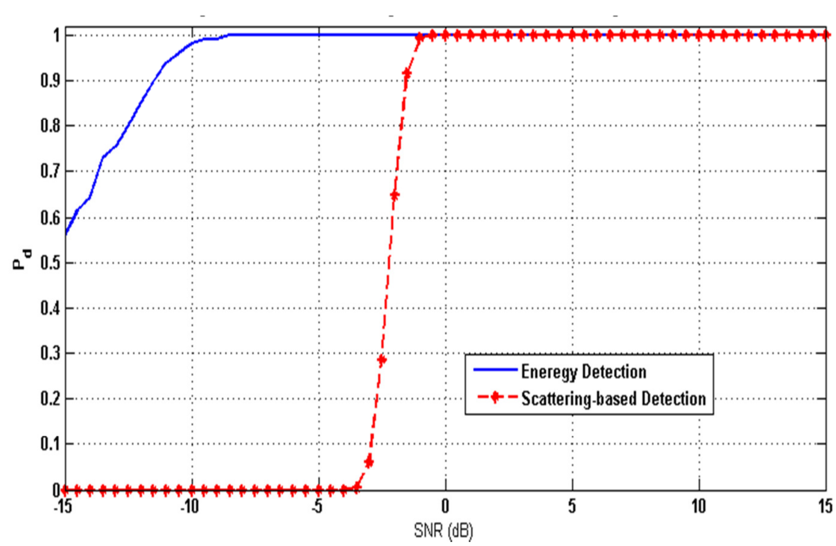


**Fig. 5.** False alarm declaration for ED and SBD when noise only considered

## 5. Conclusion

This work shows the reliability of scattering-detector over conventional energy detector for sensing the spectrum in low SNR environment despite its complexity against energy detectors. As a result of its sparse representation and by a proper choice of the wavelet basis, scattering transform can enhance significant features, reveal noise variations. Further, it can reduce the noise effect since cascaded convolution and averaging with noise results in low projection of the noise on the wavelet basis, which gives reduces the noise contribution at the scattered output.

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