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A Cooperative Cognitive Radio Spectrum Sensing Based on Correlation Sum Method with Linear Equalization

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Abstract

For moving forward toward the next generations of information technology and wireless communication, it is becoming necessary to find new resources of spectrum to fulfill the requirements of next generations from higher data rates and more capacity. Increasing efficiency of the spectrum usage is an urgent need as an intrinsic result of the rapidly increasing number of wireless users and the conversion of voice-oriented applications to multimedia applications. Spectrum sensing techniques in cognitive radio technology work upon an optimal usage of the available spectrum determined by the Federal Communication Commission (FCC). In this paper, the performance of a cooperative cognitive radio spectrum sensing detection based on the correlation sum method by utilizing the multiuser multiple input multiple output (MU_MIMO) technique over fading and Additive White Gaussian Noise (AWGN) channel is analyzed. Equalization is used at the receiver to compensate the effect of fading channels and improve the reliability of spectrum sensing. The performance is compared with the performance of Energy detection technique. The simulation results show that the detection performance of cooperative correlation sum method is more efficient than that obtained for the cooperative Energy detection technique.

Keywords

Spectrum Sensing, Cognitive Radio, MIMO, Equalization

1. Introduction

Spectrum sensing is the main feature of cognitive radio (CR) technology [1] [2]. Finding a more accurate and efficient spectrum sensing technique is the core of cognitive radio technology to develop dynamic resource management [3] [4] in future wireless networks. In 5G Cognitive radio [5] has considered as a promising technique to the spectrum scarcity problem faced by all current and the new proposed wireless technologies. Where the Cognitive radio (CR) is the task of sense, locating, identifying and detecting the idle frequency bands "spectrum holes", thus secondary unlicensed users (SUs) adjust their transmission parameters to access those bands. In order to protect primary users (PUs) from harmful interference, an accurate, robust, and rapid reaction spectrum sensor is urgently required at each CR node. Spectrum sensing has several challenges resulting from its performance and tasks such as hidden node. There are more studies in the spectrum sensing that have been proposed such as matched filtering [6], eigenvalue-based sensing [7], cyclostationary-based sensing [8] [9] [10] [11] [12], and energy detection sensing [13] [14] [15]. The energy detection method is widely used for its simplicity in calculation and ease of application. However, the spectrum sensing performance of the energy detector is severely affected by channel effects such as shadowing and fading, and noise. Cyclostationary spectrum-based sensing detection is a method for detecting primary user transmissions by exploiting the cyclostationary features of the received signals. Cyclostationary features are caused by the periodicity in the signal and are not affected by noise uncertainty like energy detection (ED). Last studies results [16] [17] shown that the detection performance of Cyclostationary spectrum sensing is excellent than energy spectrum sensing. Cooperative spectrum sensing [18]-[23] is proposed to improve the reliability spectrum sensing, increase the detection probability to better protect a primary user, and reduce false alarm probability to utilize the idle spectrum more efficiently. By cooperation, CR users can share their sensing information for making a combined decision more accurate than the individual decisions. In this paper, we will study the performance of cooperative spectrum sensing technique based on the correlation sum method [16] [24] in a multiuser multiple input multiple output (MU_MIMO) cognitive radio network and comparing the results with the cooperative energy spectrum sensing at different constrains. Using MIMO [25] [26] system will achieve spatial diversity at both transmitters and receivers and improve the error performance. We use a scenario of a centralized cooperative spectrum sensing, where a central controller (fusion center) is identified the secondary users to manage the communication and decision making; select one of the channels and ask the other secondary users to send their local sensing results through the selected channel. The fusion center collects local observation from multiple secondary uses through the reporting channel and decides the available spectrum channels using some decision fusion rule and informs the secondary users, which channels to access and determine the existence of primary users. The cooperative mechanism is applied on the received filtered signal, then we apply the auto-correlation function on the signal based on cross-sum spectrum sensing method or applying summation of the squared signal at energy detection-based spectrum sensing. The decision metric stage is applied to determine the absence or the presence of the primary user. In Section 2, we review the system model of correlation sum model. In Section 3, we describe the proposed cooperative spectrum sensing model based on correlation sum model. Simulation results are presented in Section 4. Finally, we conclude the paper in Section 5.

2. Correlation Sum Method

The correlation sum method exploits the difference between the signal spectrum and noise spectrum over the sensing bandwidth, which arises due to higher autocorrelation of the signal. The use of practical modulation schemes and the existence of RF channel guard bands tend to increase signal correlation. Also, certain primary systems are allocated much more bandwidth than the bandwidth they use to transmit symbols (e.g. radar), making the signal spectrum significantly different from flat spectrum of noise.

A simple correlation sum method [16] [24] is shown in **Figure 1**, where a band-limited received signal $x(t)$ of duration T is given as:

$$x(t) = s(t) + n(t) \tag{1}$$

where $s(t)$ is the transmitted signal and $n(t)$ is the additive white Gaussian noise. Let us consider a finite received signal samples $x(n)$, of length N, the correlated output of the received samples $x(t)$ can be written as

$$r_{xx}(t) = \frac{1}{N}\sum_{t=0}^{N-1} x(t)x(t-1), \quad t > 0 \tag{2}$$

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 $lag(l)$. 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

$$n(t) = n_c(t)\cos(2\pi f_c t) - n_s(t)\sin(2\pi f_c t) \tag{3}$$

where $n_c(t)$ and $n_s(t)$ are the in-phase and quadrature modulation components, respectively. In discrete time this is approximately can be written as

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

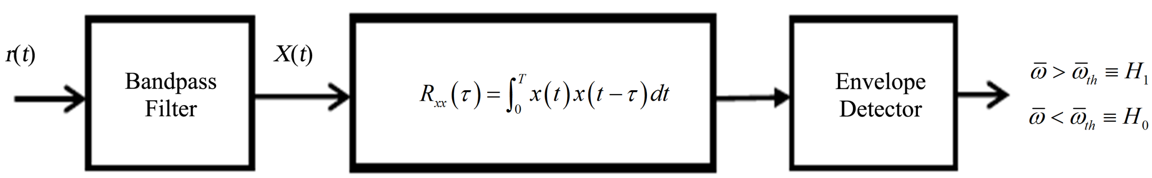

Figure 1. Block diagram of correlation sum method.

where k is the lag in samples which satisfies $k = W\tau$, where a_{ci} is the ith 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}. 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

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

The Correlation Sum method 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 as

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

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

$$\hat{R}_0' = N_0 \sum_{i=1}^{TW}\left[b_{ci}^2 + b_{si}^2\right] \tag{7}$$

And

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

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

$$\varpi = \frac{2W}{N_0}\int_0^{1/W} \hat{R}(\tau)\,\mathrm{d}\tau = \hat{R}_0' + \hat{R}_1' \tag{9}$$

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. For noise, we have

$$E\left[\hat{R}_1'\right] = E\left[U'\right] = 2TW \text{ and } E\left[\hat{R}_1'\right] = 0 \tag{10}$$

So, under hypothesis H_0, the main of the decision statistic is given as:

$$E\left[\overline{w}\right] = E\left[\hat{R}_0' + \hat{R}_1'\right] = E\left[\hat{R}_0'\right] + E\left[\hat{R}_1'\right] = 2TW \tag{11}$$

Materials While the variance of the decision statistic is given as:

$$\begin{aligned} \operatorname{var}\left[\overline{w}\right] &= \operatorname{var}\left[\hat{R}_0' + \hat{R}_1'\right] \\ &= \operatorname{var}\left[\hat{R}_0'\right] + E\left[\hat{R}_1'\right] + 2\operatorname{cov}\left[\hat{R}_0', \hat{R}_1'\right] \\ &= 4TW + 2\left(TW - 1\right) \end{aligned} \tag{12}$$

In the case when the signal is present, the bandpass signal $x(t)$ can be represented in a similar form as the noise as

$$x(t) = x_c(t)\cos\left(2\pi f_c t\right) - x_s(t)\sin\left(2\pi f_c t\right) \tag{13}$$

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 [16] [24] for hypothesis H_1 where those values are given as

$$E(\varpi) = 2TW(1+\gamma) + 2(TW-1)\rho_1\gamma \tag{14}$$

where ρ_1 is the autocorrelation coefficient of the signal for a lag of one sample where the covariance's are given as

$$Cov_1 = \left(\rho_2 + \rho_1^2\right)\gamma^2 + \rho_2\gamma \tag{15}$$

$$Cov_j = \left(\rho_{j-1}\rho_{j+1} + \rho_1^2\right)\gamma^2, \text{ where } 2 \le j \le TW-2 \tag{16}$$

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

$$\begin{aligned}\rho_j = {} & \frac{1+j\eta}{\pi} si\left\{\left(\frac{1}{\eta}+j\right)\pi\right\} + \frac{1-j\eta}{\pi} si\left\{\left(\frac{1}{\eta}-j\right)\pi\right\} \\ & -\frac{2j\eta}{\pi} si(\pi j) + \frac{\eta}{\pi^2}\left(\cos\left\{\left(\frac{1}{\eta}-j\right)\pi\right\} + \cos\left\{\left(\frac{1}{\eta}+j\right)\pi\right\}\right) - \frac{2j\eta}{\pi}\end{aligned} \tag{17}$$

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

$$si(u) = \int_0^u \frac{\sin x}{x} \mathrm{d}x. \tag{18}$$

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

$$\begin{aligned}Cov_{cc} = {} & 8(2TW-3)\rho_1\gamma^2 + 8(2TW-3)\rho_1\gamma \\ & + \sum_{j=1}^{TW-2}\left[4(2TW-3) - 8j\right]\rho_j\rho_{j+1}\gamma^2\end{aligned} \tag{19}$$

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

$$P_f = \Pr\left(\varpi > \varpi_{th} \mid H_0\right) = \frac{1}{2}\operatorname{erfc}\left[\frac{\varpi_{th} - \mu_n}{\sqrt{2}\sigma_n}\right] \tag{20}$$

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

$$P_d = \Pr\left(\varpi > \varpi_{th} \mid H_1\right) = \frac{1}{2}\operatorname{erfc}\left[\frac{\varpi_{th} - \mu_{sn}}{\sqrt{2}\sigma_{sn}}\right] \tag{21}$$

3. Cooperative Correlation Sum Spectrum Sensing System

In this section, the MIMO [27] [28] technique is used to improve the performance of Correlation Sum method of cognitive radio systems, where it enables a transmission of multiple independent data streams and suppression of interference via beamforming in the spatial domain over MIMO antenna elements to provide significant performance gains. The scenario of a Fusion Center (FC) is used to collect the local observation from multiple secondary users through the reporting channel and decides the available spectrum channels using some decision fusion rule and informs the secondary users' channels to access and determine the existence of primary users. A CR network [27] of a single primary user, secondary user with single antenna to sense the primary user signal and transmitting antenna to report to the FC is shown in **Figure 2**. The fusion center with receiving antennas is equipped with Linear equalizer [27] and correlation sum spectrum sensing. The signal received at the SU is given as

$$R_K^{(n)} = \begin{cases} w_k^{(n)} & \text{for } \mathcal{H}_0 \\ S_k^{(n)} + w_k^{(n)} & \text{for } \mathcal{H}_1 \end{cases} \tag{22}$$

where $S_k^{(n)}$ is the n^{th} PU sample received at K^{t3h} SU and $w_k^{(n)}$ is the noise signal. Both are assumed to be circularly symmetrical complex random variable. The signal received at the FC is given as

$$R_{fc} = \begin{cases} \sum_{k=1}^{K} \sum_{n=1}^{N} w_k^{(n)} & \text{for } \mathcal{H}_0 \\ \sum_{k=1}^{K} \sum_{n=1}^{N} H_k^{(n)} \overline{R}_k^{(n)} & \text{for } \mathcal{H}_1 \end{cases} \tag{23}$$

where R_{fc} is $[N_R \times N]$, $w_k^{(n)}$ *is* $[N_R \times N]$, $\overline{R}_k^{(n)}$ *is* $[N_R \times 1]$, and $H_k^{(n)}$ *is* $[N_R \times N_T]$. The total diversity path is $K \times N_R \times N_K$, where K is the number of SU, N_R is the number of FC antenna and N_T is number of SU transmitting antenna. The FC estimates the signal from K^{th} SU using the weight matrix of $H_k^{(n)}$ which is given according to analysis of equalizer (zero forcing equalizer (ZF) and Minimum Mean Square equalizer (MMSE).

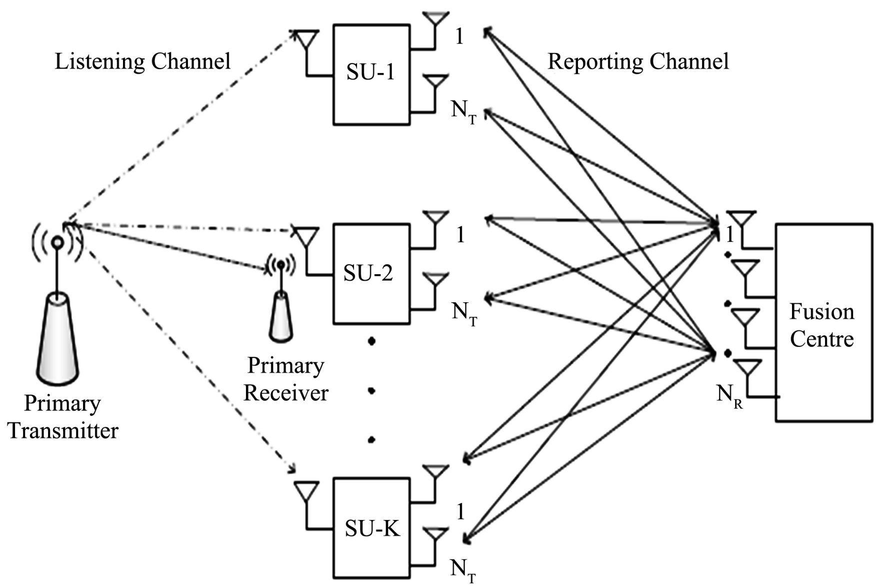

Figure 2. Cooperative MU-MIMO reporting system.

3.1. Zero Forcing Equalizer

Equalization is a signal processing technique used at the receiver to compensate the effect of fading channels. Zero forcing equalizer method determines one of the cooperative cognitive radio mechanisms which proposed to improve the reliability spectrum sensing, increase the detection probability to better protect a primary user and reduce false alarm probability to utilize the idle spectrum more efficiently. The zero forcing detectors simply derives the transmitted signals as

$$\widehat{X} = G_{zf} * Z \tag{24}$$

where Z is the received signal and G_{zf} is the pseudo-inverse of the matrix H and is given as

$$G_{zf} = H^{\mathrm{T}} = \left(H^{H} H\right)^{-1} H^{H} \tag{25}$$

3.2. Minimum Mean Square Error Equalizer

Minimum mean-squared error (MMSE) filtering is a powerful and widely used technique that minimizes the total power of the noise and ISI components in the output. MMSE equalizer determines one of the cooperative cognitive radio mechanisms, which minimizes the mean squared error between the transmitted symbol and the detected symbol at the output of the equalizer [10]. Minimum Mean Square Error algorithm detects the transmitted signal through minimizing $E\left\{\left(\widehat{X}-X\right)^{H}\left(\widehat{X}-X\right)\right\}$ the detector calculates the transmitted signal vector as

$$\widehat{X} = G_{mmse} * Z \quad \text{where} \quad G_{mmse} = R_{xz} R_{zz}^{-1} \tag{26}$$

In additional the auto-correlation matrix can be reformulated as

$$R_{xz} = E\left\{zz^{H}\right\} = \sigma_x^2 H \cdot H^{H} + \sigma_v^2 I_Q \tag{27}$$

where σ_x^2 and σ_v^2 is the signal power and noise power respectively hence MMSE matrix takes the form as

$$G_{MMSE} = H^{H}\left[H \cdot H^{H} + \frac{I_Q}{\rho}\right]^{-1} = \left[H^{H} \cdot H + \frac{I_P}{\rho}\right]^{-1} H^{H} \tag{28}$$

Evidently, with the SNR information, the MMSE detector avoids amplifying the noise and thus performs better than the ZF detector. It is worth noting that when the SNR is high, the MMSE detector approaches the ZF detector. On the other hand, the MMSE detector becomes a matched filter when the SNR is very low.

4. Results and Discussion

In this section, the analytical and Monte Carlo computer simulation results are presented to evaluate the performance of correlation sum detection method and energy detection with and without a cooperative spectrum sensing technique which includes the MIMO and equalizer schemes in the presence of several secondary users. Monte Carlo simulation is used by using 100,000 iterations with time bandwidth product (L = 500) and different values of SNR. An extensive set of simulations have been conducted in MATLAB using the system model as described in the previous sections. The results are conducted based on probability of false alarm (P_f) and probability of detection (P_d) under different values of SNR.

Figure 3 shows the receiver operating characteristics (ROC) curves that indicate the performance of energy detection using ZF equalizer in a fading noisy channel through the relation between P_d and SNR at P_f = 0.05 and L = 500. In this figure we evaluate the probability of detection of energy detection using ZF equalizer in the case of single user and in the case of multiuser. From the results it is apparent that the multiuser enhances performance better than the single user energy detection method in terms of signal detection. Where the probability of detection being optimum at SNR = −8 dB. Figure 4 indicates the performance of energy detection in the case of MMSE equalizer in a fading noisy channel in the case of single user and in the case of multiuser at P_f = 0.05 and L = 500. We see that the multiuser algorithm improves the P_d performance than the single user energy detection where it reaches to optimum at lower value of SNR (SNR = −16 dB). Figure 5 shows the comparison between multiple users and single user in correlation sum detection method using ZF equalizer at SNR = −20 dB and at SNR = −25 dB. From the results it is apparent that the Pd of the multi-users is better than in the case of the single user detection method at different values of SNR, where Pd arrives to an optimum level at low SNR values compared to single user and energy detection method.

Figure 6 shows the receiver operating characteristics curves that indicate the performance comparison of cooperative correlation sum spectrum sensing using

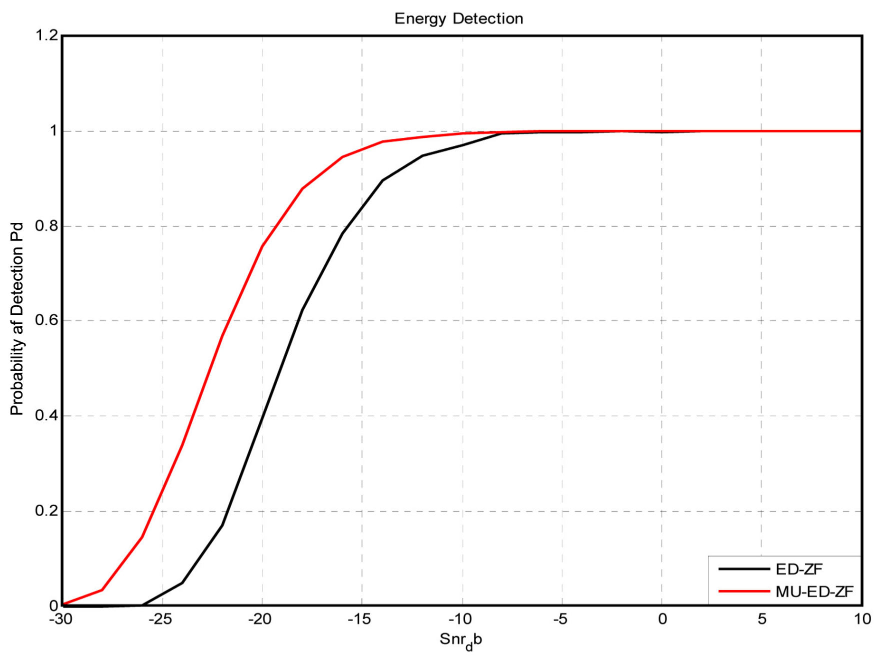

Figure 3. P_d vs SNR in ED in the case of ZF method with and without MU-MIMO.

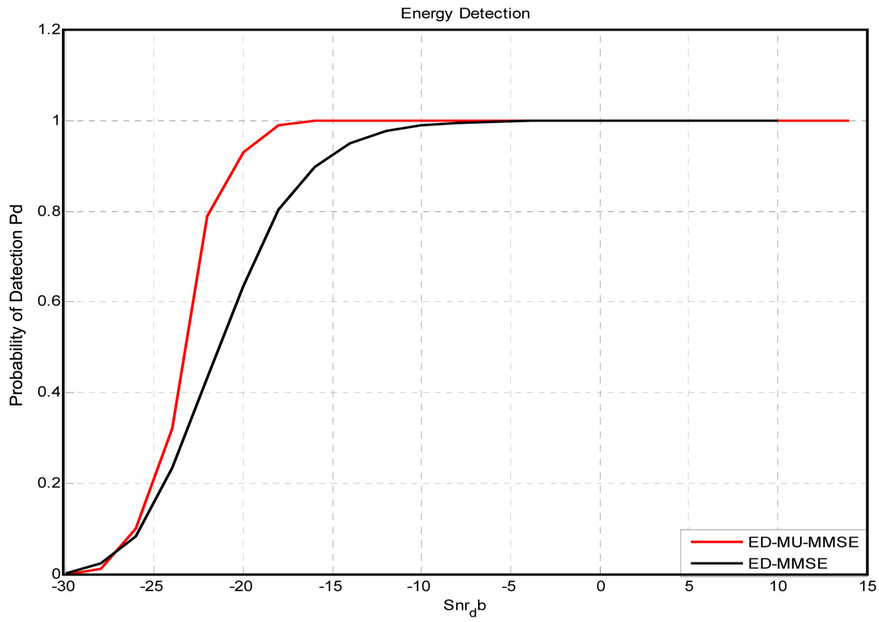

Figure 4. P_d vs SNR in Energy detection in the case of MMSE method with and without MU_MIMO.

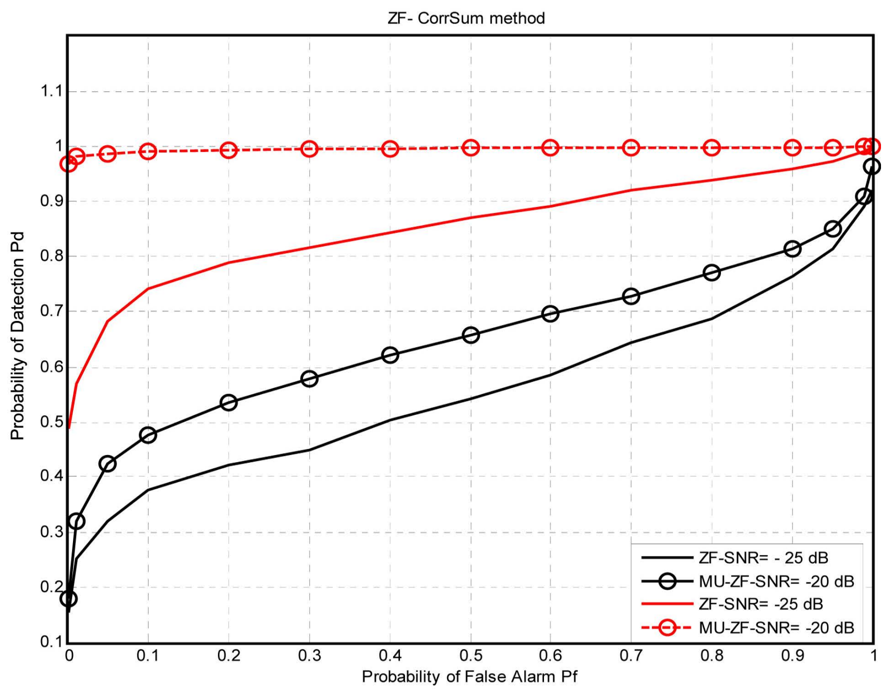

Figure 5. Pd vs P_f at correlation sum using ZF method with and without MU-MIMO.

MMSE equalizer in the case of single user and in the case of multiuser at SNR = −25 dB, −20 dB. It is apparent that the multiuser performs better performance than the single user energy detection method in terms of signal detection probability, where MMSE for multi-user have higher performance than single user and ZF method as shown in **Figure 5**.

Figure 7 and **Figure 8** show the P_d versus P_f in the case of energy spectrum

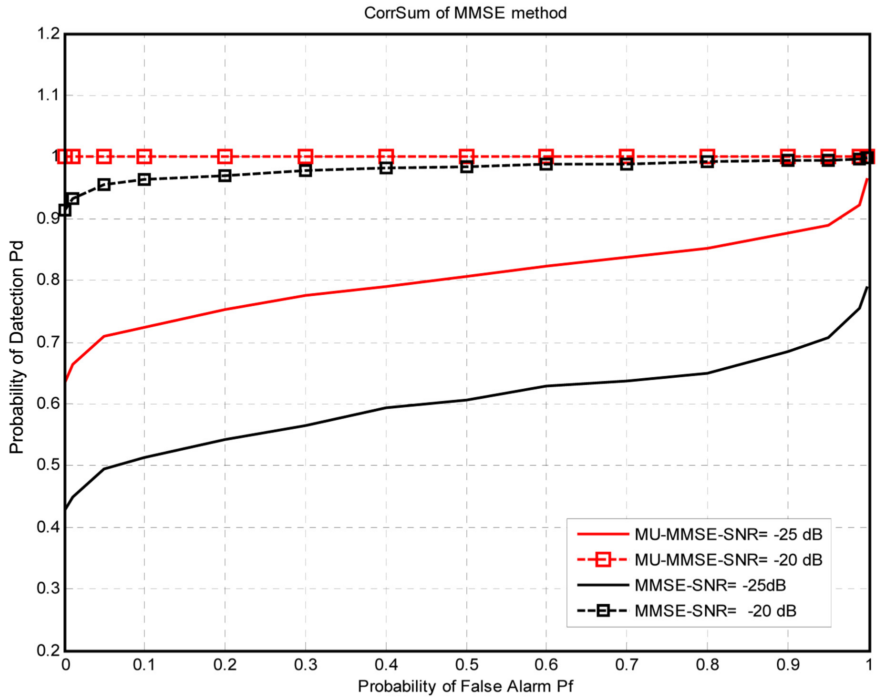

Figure 6. Pd vs P_f for correlation sum using MMSE equalizer with and without MU-MIMO.

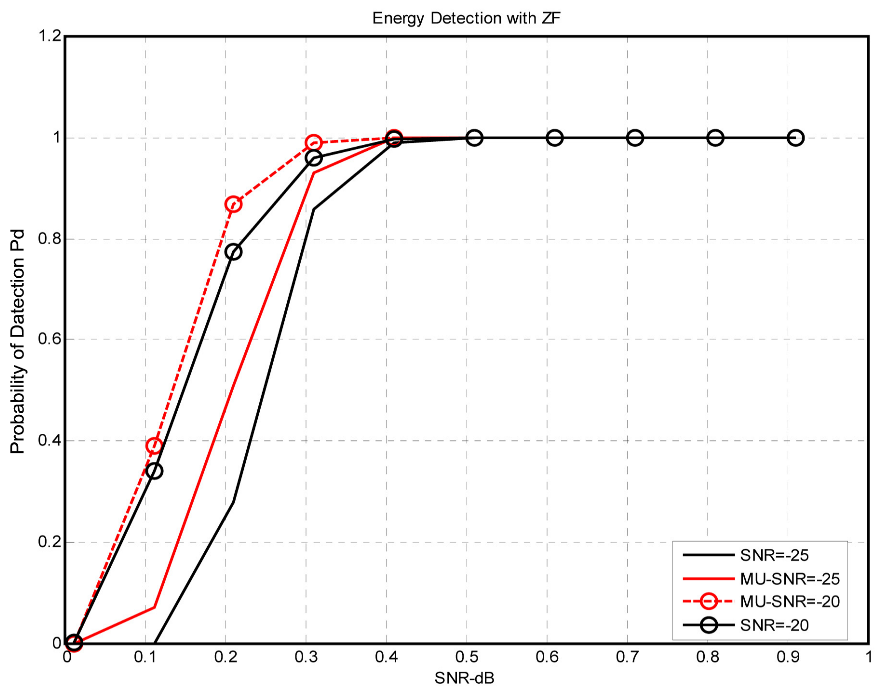

Figure 7. P_d vs P_f for energy detection using ZF equalizer with and without MU-MIMO.

sensing using ZF and MMSE equalizer respectively with and without MU at two values of SNR. From the results it is apparent that the Multi-users have better performance than the single user at SNR = −25 dB & −20 dB which shows that at higher SNR for Multi-Users achieve higher performance than single user at

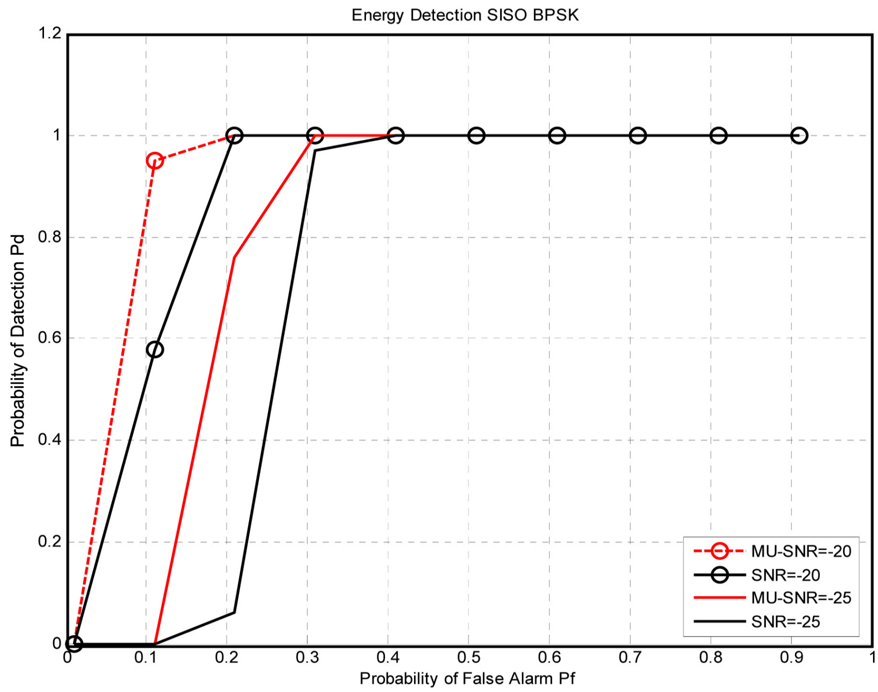

Figure 8. P_d vs P_f in ED using MMSE equalizer with and without MU-MIMO.

same values of SNR. Generally, we can see that from the results the cooperative correlation sum spectrum sensing achieves highly performance than cooperative energy detection spectrum sensing at low SNR and at low values of the false alarm probability.

5. Conclusion

In this paper, we studied the performance of a cooperative correlation sum spectrum sensing and cooperative energy detection spectrum sensing using MIMO technique and equalization techniques such as MMSE and ZF at different values of signal-to-noise ratio. The results proved that the cooperative correlation sum spectrum sensing using MU-MIMO with ZF equalizer or MMSE equalizer is more robust against interference and a fading noisy channel than cooperative energy spectrum sensing.

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Author Contributions

Conceptualization, E.G. and S.K.; Methodology, E.G. and A.L.; software, A.L. and E.G., validation, E.G., A.L. and S.K.; formal analysis, A.L. and E.G., investigation, E.G., and A.L.; resources, E.G., A.L. and S.K.; data curation, S.K.; writing—original draft preparation, A.L.; writing—review and editing, E.G. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data supporting the results of this article will be made available by the corresponding authors upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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