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AN ENHANCED CYCLOSTATIONARY SPECTRUM SENSING SCHEME USING MULTI-ANTENNA TECHNIQUE

Olagoke B. L., *Afolalu O. F., Ayoade M. A., Tijani M. A., Bamikefa I. A., Adebayo A. K.
Department of Electrical and Electronic Engineering, Federal Polytechnic, Ede. Osun State. Nigeria.
*afolaluoladele@gmail.com

ABSTRACT -Licensed spectrum band of the primary user (PU) when not in use for some time, a secondary user (SU) can utilize the unused spectrum band at that particular time so that the spectrum can be utilized efficiently. However, if the SU is unaware that the PU is utilizing the channel and begins to transmit on the channel, it causes interference in the PU's signal. Thus, this paper employs a unique technique in which multi-antenna with Cyclostationary spectrum sensing methods are combined to improve PU's signal at detection. In addition, the Maximum Selection (MS)-based energy detection spectrum sensing technique was also in comparison. The SU uses two or more receiving antennae and the Cyclostationary method which uses the signal's intrinsic period-statistics and spectral correlation to sense the PU signal's presence even when the channel is highly noisy. The system was simulated for different numbers of received antennas using M-ary Phase Shift Keying (MPSK) digital modulation schemes for signal transmission. The modulation schemes used are QPSK, 8PSK, and 16PSK. Simulation results reveal that the probability of detection increases as the number of the receiving antennae increases, and the probability of missing decreases as the number of antennae increases. Also, on average, the multi-antenna Cyclostationary method outperforms the MS-based energy detection method by about 35% in the probability of detection and about 40% in the probability of missing. The Multi-antenna Cyclostationary sensing technique helps to improve the spectrum sensing accuracy.

Keywords: - Cyclostationary, multi-antenna, primary user, secondary user, spectrum sensing

1.0 Introduction

The scarcity of radio spectrum in recent years has been attributed to the inefficiency of conventional static spectrum distribution schemes, leaving little room for future demands, if any. The issue of spectrum scarcity has gained significant attention, prompting efforts to address it through innovative solutions. Cognitive radio technology, which allows dynamic spectrum access by intelligently selecting optimal wireless channels to minimize interference and congestion, has emerged as a promising approach (Abdullah, Dawood, Abdelkareem, & Abed, 2020). Cognitive radio maximizes spectrum efficiency by enabling flexible spectrum access and has the potential to alleviate the shortage of usable radio spectrum. Since its introduction, researchers have focused on managing the radio spectrum more effectively, leading to rapid advancements in the field (Al-Hussain & Al Azawi, 2020). Cognitive radio technology has been investigated for over two decades, with innovations continuously evolving (Bagwari, Tomar, & Verma, 2013). To enhance spectral efficiency, cognitive radio networks exploit periodic intervals of unused frequency bands, known as white space or spectrum gaps, providing a solution to the spectrum scarcity problem (Bollig, Lavrenko, Arts, & Mathar, 2017). cognitive radio technology(B. Wang et al., 2010) has emerged as a breakthrough communication paradigm that can provide quicker and more reliable wireless services by more efficiently exploiting the existing spectrum band. A lack of radio spectrum in recent years has been attributed to the ineffectiveness of conventional static spectrum distribution schemes (Arjoune & Kaabouch, 2017). There is no space for future demands in this situation, assuming any exist at all. The issue of spectrum scarcity has gotten a lot of press lately, so it's getting a lot of attention. It may be described as a radio that can be configured to access dynamic spectrum by intelligently selecting the optimal wireless channel to minimize interference and congestion (Abdullah et al., 2020). Cognitive radio technology is one of the methods for maximizing the use of available spectrum, and it is currently being tested. In terms of spectrum efficiency, it is a game-changing instrument (Ahmad, 2019). Cognitive radio technology, by enabling complicated spectrum access, can alleviate the shortage of useable radio spectrum. Ever since the introduction of this groundbreaking technology, researchers have been trying to make it possible to manage the radio spectrum. Because of this, this field of research has advanced rapidly, with significant advances (Al-Hussain & Al

Azawi, 2020). Cognitive radio technology, which has been extensively investigated by the scientific community for over two decades, is one answer to these and other problems (Bagwari et al., 2013). To improve spectral efficiency, cognitive radio networks have been developed as a potential technique for accessing periodic intervals of empty frequency bands, termed white space or spectrum gaps (Bollig et al., 2017). IoT devices with opportunistic spectrum access (Cahyo et al., 2013) may interact with each other and with the internet while the main user is not present using cognitive radio (CR). It improves band utilization and enhances spectrum resource allocation, cryptosystem utilizes spectrum allocation to limit unauthorized access to ensure confidentiality, encryption, and program integrity (Cao & Liu, 2015). They can automatically identify which communication channels are in use and immediately migrate into the unoccupied ones while avoiding the ones that are. "Cognitive radio" is a type of wireless communication in which the transmitter can intelligently identify which communication channels are in use and which ones are not. It then switches to the channels that are free and avoids the busy ones. The Radio-frequency (RF) spectrum is optimally used in this way, with the least amount of disruption to other users (Chaudhari et al., 2016). Continuously re-evaluate the parameters of its operations, and learn from its experience. Cognitive radio (CR) refers to a radio that is aware of its operational and geographical surroundings as well as its internal state. Dynamically and autonomously, it can change its operating settings as well as its procedures, and it can also learn from its past experiences. Several methods can be used to identify primary users.

2.0 Related Works

Advancements in radio spectrum management have driven extensive research in this field. In Üstok's (2010) study, spectrum sensing techniques for cognitive radio systems with multiple antennas were explored. The method used involved cyclostationary feature detection and energy detection, focusing on enhancing performance with multi-antenna systems. The results showed improved detection accuracy and reduced interference in cognitive radios, particularly under low signal-to-noise ratio (SNR) conditions. However, the study's main shortcoming was the complexity and high computational demand of the multi-antenna setup, making it less feasible for real-time, large-scale applications.

Chen, Gibson, and Zafar (2008) introduced a method for detecting cyclostationary spectrum density using Kaiser window functions. This method leverages spectral autocorrelation to detect weak signals, even in the presence of noise. The Kaiser window enhances the signal detection process by optimizing between the main lobe width and side lobe amplitude, making it more effective for spectral analysis. The study highlights the efficiency of the method for spectrum sensing, although challenges include higher computational demands due to extended observation periods.

Saggar and Mehra (2013) used the FREquency SHift (FRESH) method, which applies filters to optimally estimate cyclostationary signals by leveraging spectral coherence. The method improved spectrum sensing in low signal-to-noise ratio (SNR) environments, allowing more accurate detection of weak signals. The results demonstrated enhanced performance in detecting cyclostationary signals under noisy conditions. However, a notable shortcoming is the increased computational complexity required for filter optimization and handling spectral coherence, which may limit its practical application in real-time scenarios.

Abdullah et al. (2020) hybridized energy detection and cyclostationary sensing techniques by employing the Fast Fourier Transform (FFT) for energy detection and the Sliding Discrete Fourier Transform (SDFT) for cyclostationary detection. The simulations conducted under multipath fading channels showed improved detection performance in both cooperative and non-cooperative scenarios. However, the method's complexity may pose a limitation, requiring significant computational resources and potentially increasing latency, which could hinder real-time applications in dynamic spectrum environments.

Elnahas and Elsabrouty (2017) proposed a compressed spectrum sensing algorithm using the Fast Fourier Transform Accumulation Method (FAM) and multi-task compressive sensing for cooperative cyclostationary systems, reducing high sampling rates in wideband signal sensing. The method showed improved detection accuracy and spectral efficiency. However, its main shortcomings include computational complexity and reliance on cooperative networks, which can introduce synchronization issues and communication overhead, reducing sensing accuracy in dynamic environments.

3.0 Materials and Methods

3.1 System model for the MIMO antenna signaling with MPSK modulation

In a multi-antenna cognitive radio network, both the transmitter (i.e. PU) and receiver (i.e. SU) are equipped with multiple antennas which represent a $N_t \times N_r$ MIMO antenna configuration. In this paper, the PU uses $N_t = 4$ antennas to transmit while the SU uses N_r number of antennas for sensing (or receiving) the PU's signal a valueN_r varies between and 6 antennas. Downright signaling system can be represented by the matrix model equation that follows;

$$\begin{bmatrix} r_1 \\ \vdots \\ r_{Nr} \end{bmatrix} = \begin{bmatrix} h_{11} & \dots & h_{1Nt} \\ \vdots & \ddots & \vdots \\ h_{Nr1} & \dots & h_{NrNt} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_{Nt} \end{bmatrix} + \begin{bmatrix} n_1 \\ \vdots \\ n_{Nr} \end{bmatrix} \quad (1)$$

Equation (1) can be rewritten in vector form as:

$$\text{Bold}\boldsymbol{r} = \boldsymbol{Hx} + \boldsymbol{n} \quad (2)$$

Where $\boldsymbol{r}$ denotes N_r copies of the received signal, $\boldsymbol{x}$ denotes the N_t – dimensional transmitted symbol, e N_r – dimensional additive white Gaussian noise (AWGN) vector; and $\boldsymbol{H}$ represents the fading channel matrix which is assumed to be Rayleigh distribution. Each element of $\boldsymbol{H}$ denotes the h_{ij} channel gain from the transmit antenna j to receive antenna i..he transmitted symbol x_j is assumed to be M-ary Phase Shift Keying (MPSK) modulated where M represents the modulation level. The value for M is taken to be 4 denoting QPSK modulation, which is commonly used in various applications.

3.2 Multi-antenna Maximum Selection (MS)-based energy detection technique

The energy content of a received signal can be obtained as:$E_t = \sum_{n=1}^{N} |x(n)|^2$
(3)

where N denotes the number of symbols in the signal which represents the length of the signal. The value of E_t is compared with a predetermined threshold Calabasas:

$$\text{Cap}E_t \leq \lambda \quad (4)$$

The MS-based energy detection technique with MIMO antenna is represented in the block diagram of Figure 1. The SU receives N_r copies of the detected signal of which each signal copy has a fading level different from the others. Then, the maximum absolute value of symbols in each signal copy is computed.

The signal copy that gives the maxim absolute value $Max(|r_i|)$, is selected and forwarded to the energy detector which computes the signal energy using Eq. (3). Then, the value E_t is forwarded to the decision block to decide whether PU signal is detected or not.

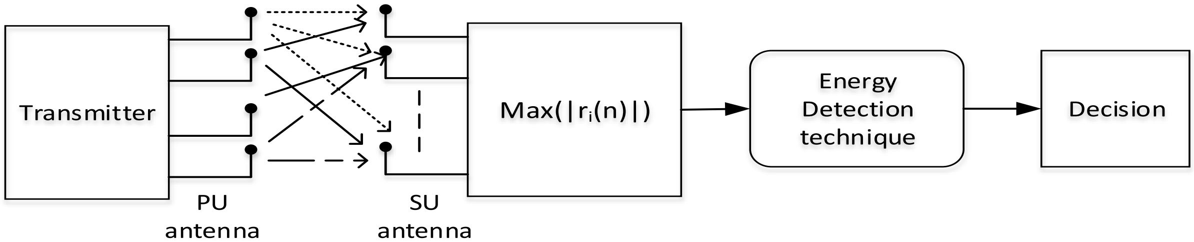

Figure 1: Block diagram of MS-based energy detection technique with MIMO antenna

3.3 Multi-antenna cyclostationary detection technique

A modulated signal $r(t)$ is considered to be a periodic signal or a cyclostationary signal if its mean and autocorrelation exhibit periodicity as:

$$C_r(t+\tau/2, t-\tau/2) = \sum_\alpha \left[\frac{1}{T}\int_{-1/T}^{1/T} C_x(t+\tau/2, t-\tau/2)\, e^{j2\pi\alpha t} dt\right] e^{j2\pi\alpha t} \quad (5)$$

$$= \sum_\alpha C_r^\alpha(\tau)\, e^{j2\pi\alpha t} \quad (6)$$

where α denotes the cyclic frequency, which is to be known to the SU. Expressing C_r^α in frequency domain gives the Spectral Correlation Function (SCF) as:

$$S_r^\alpha(f) = \int_{-\infty}^{\infty} C_r^\alpha(\tau) e^{-j2\pi f\tau} d\tau \quad (7)$$

The cyclostationary detection technique with MIMO antenna is represented in the block diagram of Figure 2.

Copies of the received signal picked up by the SU antennas are passed to the maximum likelihood detector.

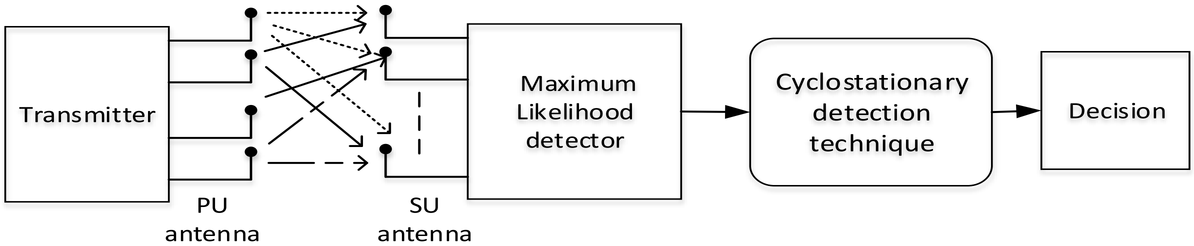

Figure 2: Block diagram of cyclostationary detection technique with MIMO antenna

3.4 System Simulation

The flowchart and algorithm for the simulation of the systems are shown in Figure 3 and Algorithm 1. MATLAB programs were written from the algorithm and numerical results were obtained. The input data to the system were randomly generated bits.

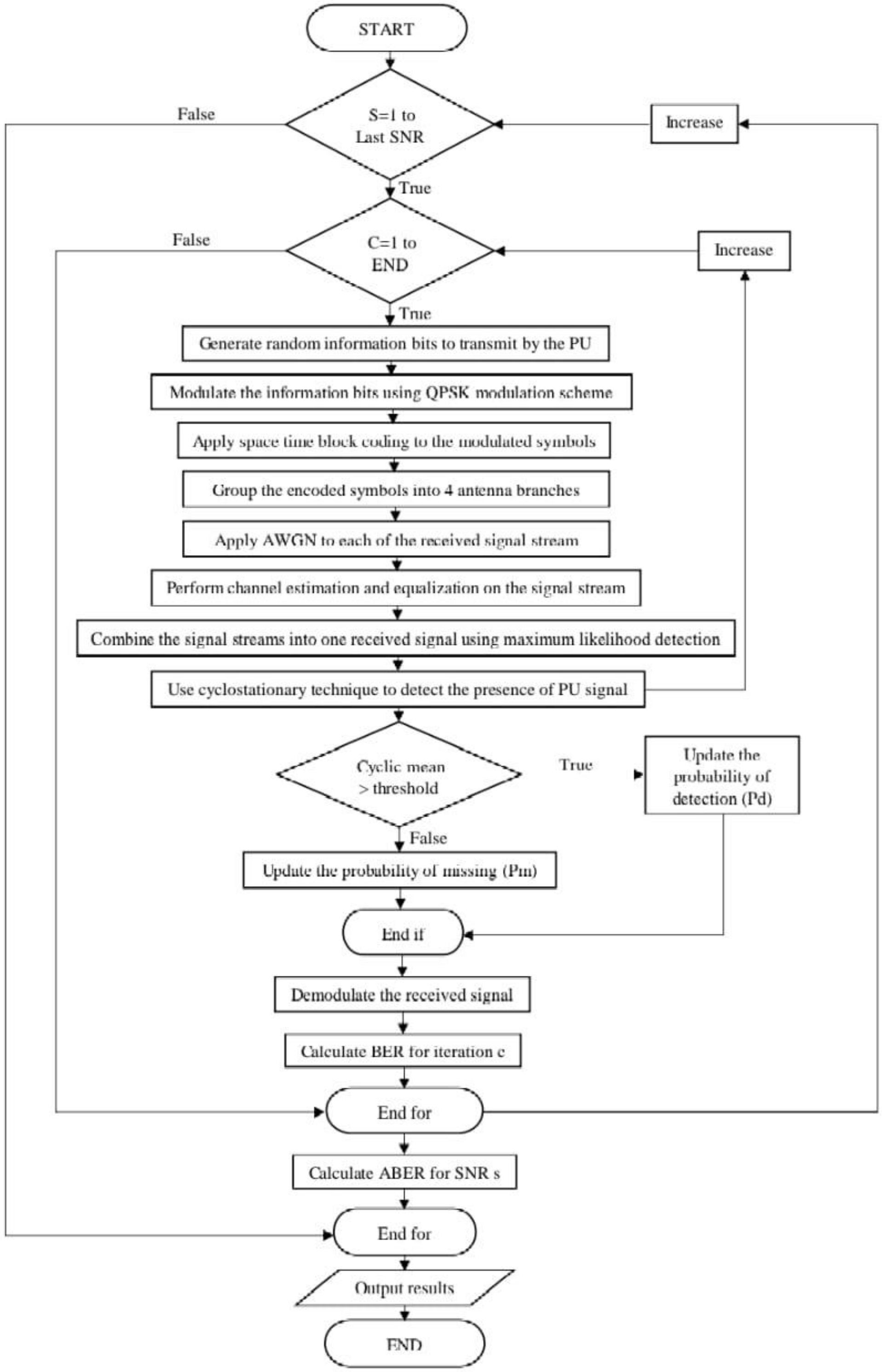

Figure 3: Flowchart for the system implementation

Table 1: Simulation parameters of the System

Parameter	**Value**
Modulation scheme	QPSK
Number of transmit (or PU) antennas	4
Number of receive (or SU) antennas	[2, 3, 4, 5, 6]
Space-time block code (STBC) rate	0.5
STBC length	8
Carrier frequency	2.0 GHz
Threshold for cyclostationary detection	6.5
Fundamental cyclic period	25
Number of iterations	100
Length of information bits	1000

3.5 System Performance Evaluation Metrics

Three metric indices were employed to evaluate the proposed scheme's technique. These metrics are probability of detection (P_d), probability of missing (P_m), and average bit error rate (BER).

3.5.1 Probability of Detection (P_d): This is the probability of the spectrum sensing technique to detect the PU signal correctly. The P_d increases with increasing received signal strength or SNR. The probability of detection is obtained by summing the number of times the spectrum sensing technique correctly detects the PU signal's presence and then dividing the sum by the number of iterations or counts.

3.5.2 Probability of Missing (P_m): This is the probability that the PU signal presence cannot be detected by the spectrum sensing technique. The P_m decreases with increasing received signal strength or SNR. The probability of missing is obtained by summing how many times PU signal's presence is missed by the spectrum sensing technique and then dividing the sum by the number of iterations or counts.

3.5.3 Bit Error Rate (BER): This is calculated by dividing the number of bits received in error by the total number of bits received.

3.6 Results and Analysis

Performance of Spectrum Sensing Techniques using Multi-Antenna Receiver

We present in this section the simulated result analyses of the proposed multi-antenna spectrum sensing strategies. The number of transmitting antennas is given by N_t while the number of receiving antennas is represented by N_r. Hence, a multi-antenna configuration is represented by $N_t \times N_r$ MIMO. The PU transmits using N_t and QPSK modulation while the SU receives or senses using N_r. Figure 4 shows the probability of detection performance in terms of SNR for the cyclostationary detection technique for N_t = 4 and N_r varied between 2 and 6 antennas. The results indicate that all the MIMO configurations, that is, 4x2 MIMO, 4x3 MIMO, 4x4 MIMO, 4x5 MIMO, and 4x6 MIMO achieved 1.0 (or 100%) probability of detection from -4 dB and above.

However, at a lower SNR (signal-to-noise ratio) of -15 dB, the 4x2 MIMO, 4x3 MIMO, 4x4 MIMO, 4x5 MIMO, and 4x6 MIMO achieved 0.5236, 0.7308, 0.8636, 0.9352 and 0.9608 probability of detection, respectively. The results reveal that the cyclostationary detection technique achieves better probability of detection with increasing number of N_r antennas. Probability of detection for the maximum selection (MS)-based energy detection spectrum sensing technique proposed by Ustuk (2010) was also investigated and the results shown in Figure 5. The results reveal that all the MIMO antenna configurations achieved a 1.0 (or 100%) probability of detection from 8 dB and above. However, at a lower SNR of -10 dB, the 4x2 MIMO, 4x3 MIMO, 4x4 MIMO, 4x5 MIMO, and 4x6 MIMO achieved 0.0960, 0.5960, 0.8848, and 1.0000 probability of detection, respectively.

The results demonstrate the ability of MS-based energy detection technique to achieve better probability of detection with increasing number of N_r antennas.

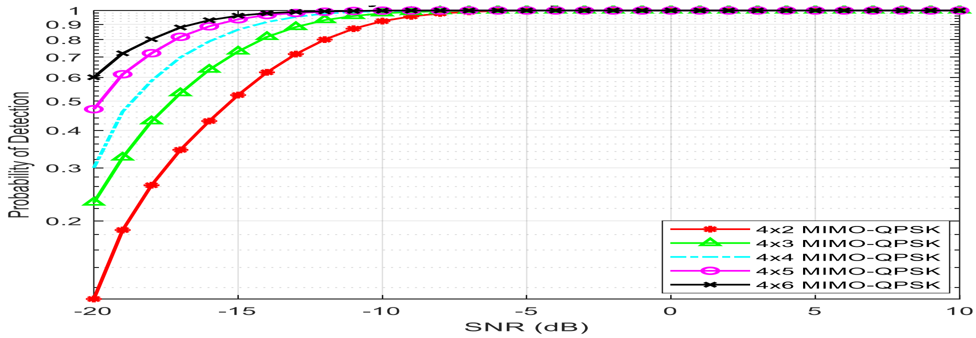

Figure 4: Probability of Detection versus SNR for cyclostationary detection technique

The results show that increasing the number of receiving antennas (N_r) in MIMO configurations improves the probability of detection for both cyclostationary and MS-based energy detection techniques.

Cyclostationary detection achieves better performance in low SNR environments, with detection improving from 52.36% (4x2 MIMO) to 96.08% (4x6 MIMO) at -15 dB. MS-based detection reaches 100% detection at 8 dB or higher but performs poorly at lower SNRs. In practice, larger antenna arrays enhance detection reliability in cognitive radio networks, particularly under weak signal conditions.

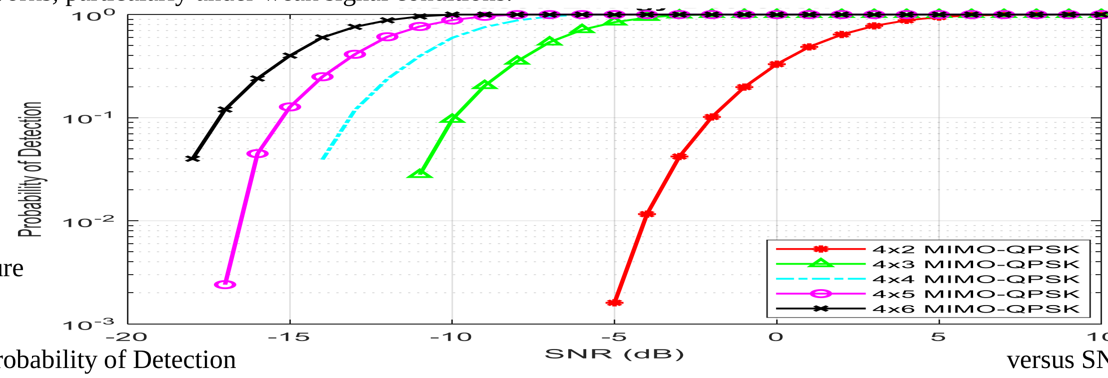

Figure 5: Probability of Detection versus SNR for maximum selection (MS)-based energy detection spectrum sensing technique

Figure 6 shows the probability of missing performance in terms of SNR for the cyclostationary detection technique. The results show that all the MIMO configurations achieved (or 100%) probability of missing from -4 dB and above. At lower SNR of -12 dB, probability of missing values 0.1996, 0.0708, 0.0232, 0.0092 and 0.0064 were obtained with 4x2 MIMO, 4x3 MIMO, 4x4 MIMO, 4x5 MIMO and 4x6 MIMO, respectively. For the MS-based energy detection technique as shown in Figure 7, all the MIMO configurations achieved (or 100%) probability of missing from 8 dB and above. However, at SNR of -12 dB, the 4x2 MIMO, 4x3 MIMO, 4x4 MIMO, 4x5 MIMO, and 4x6 MIMO achieved probability of missing values 1.0000,1.0000,0.7624, 0.3904 and 0.1200, respectively. The results reveal that both the cyclostationary detection and MS-based energy detection techniques achieve better probability of detection with increasing number of N_r antennas.

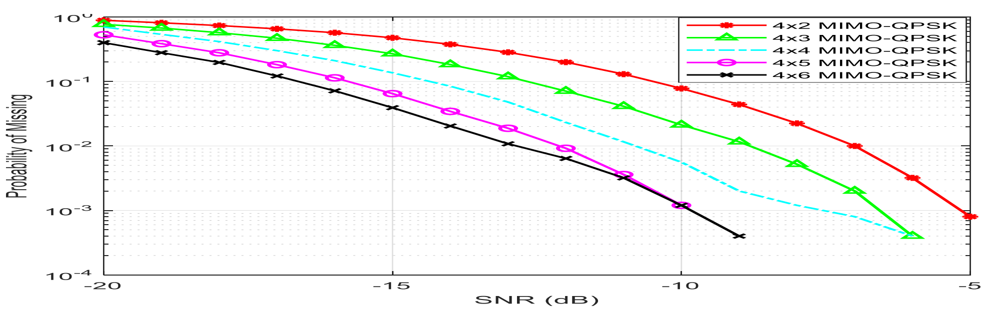

Figure 6: Probability of Missing versus SNR for cyclostationary detection spectrum sensing technique

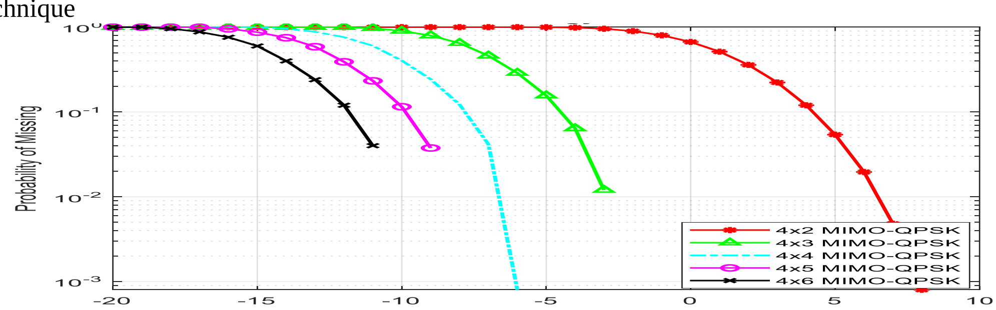

Figure 7: Probability of Missing versus SNR for MS-based energy detection spectrum sensing technique

The effect of MIMO antenna configuration on Average Bit Error Rate (ABER) performance for the cyclostationary detection is shown Figure 8.

The trend is that the ABER reduces with increasing SNR irrespective of the spectrum sensing technique.

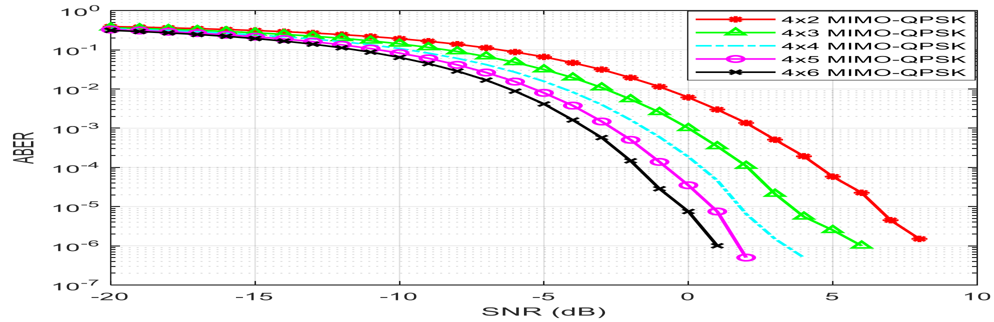

Figure 8: Average BER versus SNR for cyclostationary detection spectrum sensing technique

The results indicate that increasing the number of receiving antennas (N_r) reduces the probability of missing in both detection techniques. For cyclostationary detection at -12 dB, the probability of missing decreases from 19.96% (4x2 MIMO) to 0.64% (4x6 MIMO). Similarly, for MS-based energy detection, it drops from 100% (4x2 and 4x3 MIMO) to 12% (4x6 MIMO). These findings suggest that using more antennas enhances detection accuracy, particularly in low-SNR environments, improves detection accuracy, reducing the probability of missing signals, especially in low-SNR conditions, enhancing system reliability.

3.7 Conclusion

This work is an enhanced cyclostationary spectrum sensing scheme using a multi-antenna technique. The system was simulated for different numbers of received antennas using M-ary Phase Shift Keying (MPSK) digital modulation schemes for signal transmission. Simulation results showed that the multi-antenna cyclostationary detection technique gives a higher probability of detection and a lower probability of missing. The simulations revealed that increasing the number of receiving antennas improved detection accuracy, reducing the probability of missing signals and lowering the Average Bit Error Rate (ABER). The results show that both cyclostationary and MS-based energy detection techniques benefit from larger antenna arrays, especially in low-SNR environments. These findings make the technique highly effective for real-world applications, such as cognitive radio networks (CRN), where reliable and efficient spectrum sensing is essential.

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