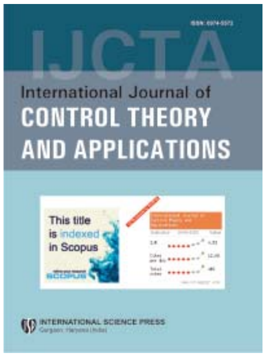

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Implementation of Spectrum Sensing Techniques in Cognitive Radio Networks

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Abstract: Spectrum sensing is a crucial task in Cognitive Radio Networks(CRNs) to improve spectrum utilization for wireless communications. This paper presents recent advances in spectrum sensing and the detection process of Primary User (PU) at low SNR value by compressive sampling using energy detection technique in CR. In this paper, the sub-Nyquist technique such as compressive sensing is considered to detect the spectrum usage without the prior information of sparsity. Initially wideband QPSK signal is generated with a length of N samples and 50% compressed with KxN measurement matrix (K < N). Minimum energy signal is detected from the compressed signal then reconstructed by using l1 minimization algorithm. Experimental results show that the proposed scheme detects the PU even in the presence of noise uncertainties. Experimental results show an improvement over traditional energy detection technique in terms of Probability of detection (P_d) and Probability of false alarm (P_{fa}).

Keywords: *CognitiveRadio, SpectrumSensing, Compressive sensing, l1 minimization, Signal Recovery*

1. INTRODUCTION

Cognitive Radio(CR) is a promising solution to improve spectrum utilization in wireless communications [2]. In CR, secondary users can detect and utilize the unlicensed spectrum without disturbing the Primary User(PU); this ability is called spectrum sensing, which is the most critical issue in Cognitive Radio Networks(CRN) [3].CRN is used to sense wideband spectrum continuously using energy detector, it will divide wideband into number of narrow bands energy detector will scan every narrowband continuously so find the white holes for SU. The computations involved in sensing are high, which increase the hardware complexity. Hence, the cost of system is increased. To overcome this problem we apply compressive sampling theory to our Cognitive Radio Network to reduce number of calculations by taking compressed samples for sensing.

Sharma, Shree Krishna [1] described compressive sensing and its applications in CRNs, signal recovery from undetermined linear systems using various signal recovery algorithms like Basis Pursuit, OMP algorithm and its complexity. Sun Hongjian [2] described various wideband spectrum sensing algorithms, challenging issues, sub-Nyquist techniques, including compressive sensing and multi-channel sub-Nyquist sampling techniques. E.Axell, Geert lews, H.v. poor [3] presented about detection of primary user when weak signal is present in spectrum using different methods such as energy detection. Tevfik Yucek and H Arslan [4] presented different spectrum sensing methods, challenges, cooperative sensing. The Authors [5][6][12] described compressed sensing techniques for spectrum hole identification, wavelet based edge detector, the proposed novel sensing algorithms were robust to noise and can afford reduced sampling rates. Y.zeng,Y.c. liang [7] proposed spectrum sensing technique using the likelihood ratio test for energy detection , Matched detector, cyclostationary detection, cooperative sensing for multiple receivers. Shancang Li, Xinheng Wang, Xu Zhou and Jue Wang [8] proposed about the too high sampling rates cause immense computational costs and sensing problems. The prefect reconstruction from fewer samples was achieved by a blind signal reconstruction algorithm which explore *l*p- norm. Emmanuel Candes, Justin Romberg, and Terence Tao [9][10] *l*1 magic gives an idea about representation of sparse signal from original signal, primary dual algorithm and reconstruction of original signal from sparse samples using *l*1 minimization process.

2. SPECTRUM SENSING TECHNIQUES

Spectrum sensing techniques are classified into four categories. The first two categories are coherent and non-coherent detection techniques. In coherent detection, a priori knowledge of the primary user signals is required, which will be compared with the received signal to coherently detect the primary signal. In non-coherent detection, no priori knowledge of primary user signals is required for coherent detection. The last two broad categories are narrowband and wideband detection techniques based on the bandwidth of the spectrum[13].

2.1. Narrow band Spectrum Sensing

These algorithms can be used to detect the primary transmitters including matched filtering, energy detection and cyclostationary feature detection, as shown in Fig. 1, 2 and 3.

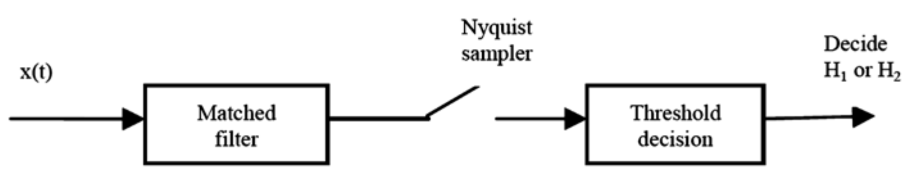

Figure 1: Block diagram for matched filtering

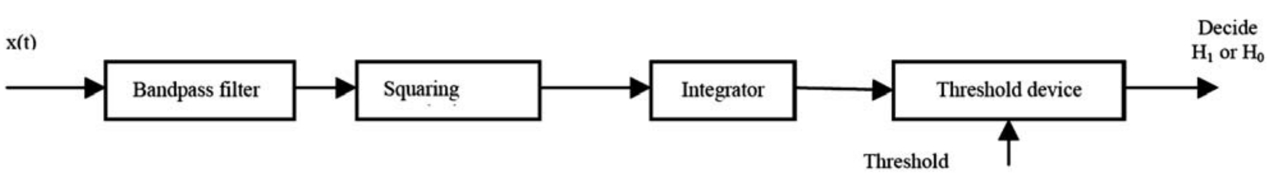

Fig 2: Block diagram for energy detection

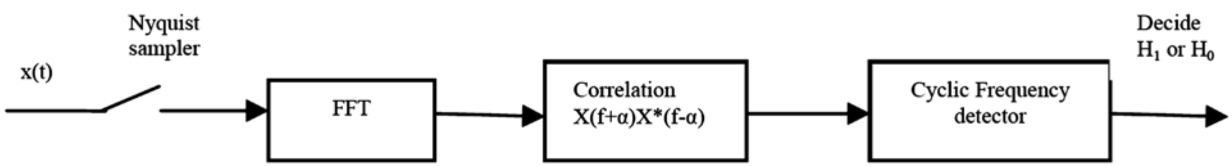

Figure 3: Block diagram for cyclostationary feature detection

In this case the frequency range is narrow such that the required bandwidth is less than the coherence bandwidth of the channel.

1. **Matched filter Detection:** Matched filtering approach is simple and less computational complexity but it requires prior knowledge of the primary user[4]. This is an optimal approach for spectrum sensing since it maximizes the signal-to-noise ratio (SNR) in the presence of additive noise, by correlating the received signal with a template for detecting the presence of a known signal which increases the implementation complexity.

2 **Energy Detection:** Energy detection is a non-coherent detection technique that does not require prior knowledge of the PUs. So it is easy to implement and has less computational complexity and it has poor detection performance under low Signal to Noise Ratio conditions. In this case the received signal can be written as

$$y(n) = s(n) + w(n)$$

where $$n = 0,1,2,....\mathrm{N} \tag{1}$$

where $s(n)$ is the signal to be detected, $w(n)$ is the additive white Gaussian noise(AWGN) sample, and n is the sample index. The decision metric for the energy detector can be written as

$$\mathrm{M} = \sum_{n=0}^{\mathrm{N}} |y(n)| \wedge 2 \tag{2}$$

Where N is the size of the observation vector. The occupancy of the band can be decided by comparing the decision metric M with a threshold λe. This is equivalent to distinguishing between the following two hypotheses.

$$\mathrm{H}_0 : y(n) = w(n) \tag{3}$$

$$\mathrm{H}_1 : y(n) = s(n) + w(n) \tag{4}$$

The performance of the detection algorithm can be evaluated by the Probability of detection P_d and Probability of false alarm P_{fa}. They can be formulated as

$$\mathrm{P}_d = \mathrm{P}_r(\mathrm{M} > \lambda_e \mid \mathrm{H}_1) \tag{5}$$

$$\mathrm{P}_{fa} = \mathrm{P}_r(\mathrm{M} > \lambda_e \mid \mathrm{H}_0) \tag{6}$$

P_{fa} should be kept as small as possible in order to prevent under utilization of transmission opportunities. The decision threshold λ_e can be selected for finding an optimum balance between P_d and P_{fa}. To obtain a certain false alarm rate, the threshold has to be chosen.

3. **Cyclostationary Feature Detection:** Cyclostationary Feature detection is valid in low SNR region and needs partial prior knowledge and high computational cost. It detects various types of primary signals by exploiting their cyclostationary features [6].

2.2. Wideband Spectrum Sensing

Wideband sensing technique is used to sense a frequency bandwidth that exceeds the coherence bandwidth of the channel [4]. It can be classified into two types: Nyquist wideband and sub-Nyquist wideband sensing. The first technique processes digital signals taken at or above the Nyquist rate, whereas the second one acquires signals using a sampling rate lower than the Nyquist rate[11]. In this paper, wide band spectrum sensing algorithms are implemented.

1. **Compressive Sensing:** Compressive sensing is one of the techniques of sub-Nyquist wideband sensing and it has low sampling rate, signal acquisition cost and sensitive to design imperfections [1] [5][7]. Due to low spectrum utilization in wideband spectrum, we consider a spectrum sensing scheme based on compressive sampling of the wide-band using *l*-1 minimization algorithm[12].

3. PROPOSED METHOD

Input is random bit stream which is converted into a QPSK (Quadrature Phase Shift Keying) signal with size N which is denoted by $s_1(n)$.

Step 1: Generate a random measurement matrix (A) with size of KXN and satisfies orthogonal property ($AA^T = 1$). Where K is number of observations. The compression rate depends on K value.

Step 2: Generate a compressed matrix z by following equation

$$z = A^* s_1 \tag{7}$$

Step 3: The Additive white Gaussian noise $w(n)$ is added to compressed signal, combined signal is denoted by $y(n)$.

Step 4: Calculate the energy of combined signal y by

$$E = \sum_{n=0}^{N} |y|^{\wedge} 2 \tag{8}$$

Step 5: From the energy of signal derive the test statistics

$$E = \frac{1}{k} \sum_{n=0}^{K} |y|^{\wedge} 2 \tag{9}$$

Step 6: By assuming probability of false alarm determine the threshold value of energy detector which is denoted by τ by following equation

$$\tau = Q \quad (P_{fa} / \sqrt{K}) + 1 \tag{10}$$

Step 7: Compare the test statistics T with Threshold τ. If T exceeds τ, detection is declared as H_1. Otherwise, the decision is made that no signal is present H_0. From the detection mechanism two probabilities are calculated as

$$P_d = P_r(T > \tau/H_1) \tag{11}$$

$$P_{fa} = P_r(T < \tau/H_0) \tag{12}$$

Where H_1, H_0 are Hypothesises of detection mechanism where H_1 means primary user is present in the band, H_0 means primary user absent in the band.

Step 8: Original signal is recovered from the sparse signal. Here sparse signal is minimum energy signal which is derived from following equation

$$x_0 = A^T * z \tag{13}$$

Step 9 : The original signal is recovered from minimum energy signal by using primal-dual algorithm. In primal-dual algorithm residuals of signal are compared with l-1 norm vector of x_0. The residual of primal-dual algorithm is given by

$$R_{Primal} = Ax_0 - z \tag{14}$$

$$R_{Central} = \begin{bmatrix} \lambda_1 \ f_1 \\ \lambda_2 \ f_2 \end{bmatrix} - (1/\tau) \tag{15}$$

$$R_{Dual} = \begin{bmatrix} \lambda_1 - \lambda_2 & + A'v \\ 1 & -\lambda_1 - \lambda_2 \end{bmatrix} \tag{16}$$

Where λ_1, λ_2 and v are the duals to x_0 which are solved by either using conjugate gradient method or linear solve method. The parameter τ is responsible for iteration and step size (s).

Step 10: The original signal is recovered as $x_p = x_0 + s * dx$ by number of iterations.

Table 1
Parameters Table

Parameters	*Values of parameters*
Carrier frequency(fc)	[64,32,21,16,12.33]
Number of samples(N)	512 samples
Number of observations(K)	256 samples
Orthogonal Matrix(A)	256x512
Original signal($S_1(n)$)	2560 samples
Compressed signal($Z(n)$)	1280 samples
Energy of the signal($Y(s)$)	[11.0012]
Threshold value(τ)	1.0801
Minimum energy signal(x_0)	2560 samples
Probability of detection(P_d)	0.9
Probability of false alarm(P_{fa})	0.1
Signal to Noise Ratio(SNR)	(-14 dB to 0 dB)
SNR wall	Minimum SNR of signal below which the detection fails
Additive White Gaussian Noise	[-2.7443 to 3.0387]

The input parameters for the proposed work are shown in Table 1.

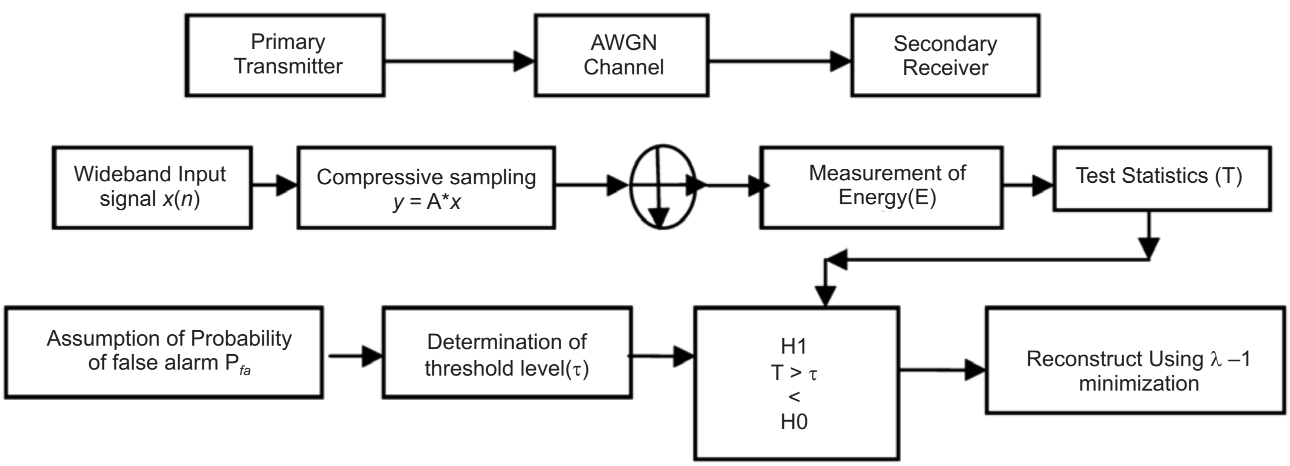

Figure 4: Block diagram for compressive sensing

The block diagram and flow chart of proposed work is shown in Fig. 4 and Fig. 5. It clearly describes step by step procedure and the functional blocks of compressive spectrum sensing system which explains the process for compression and recovery of original signal.

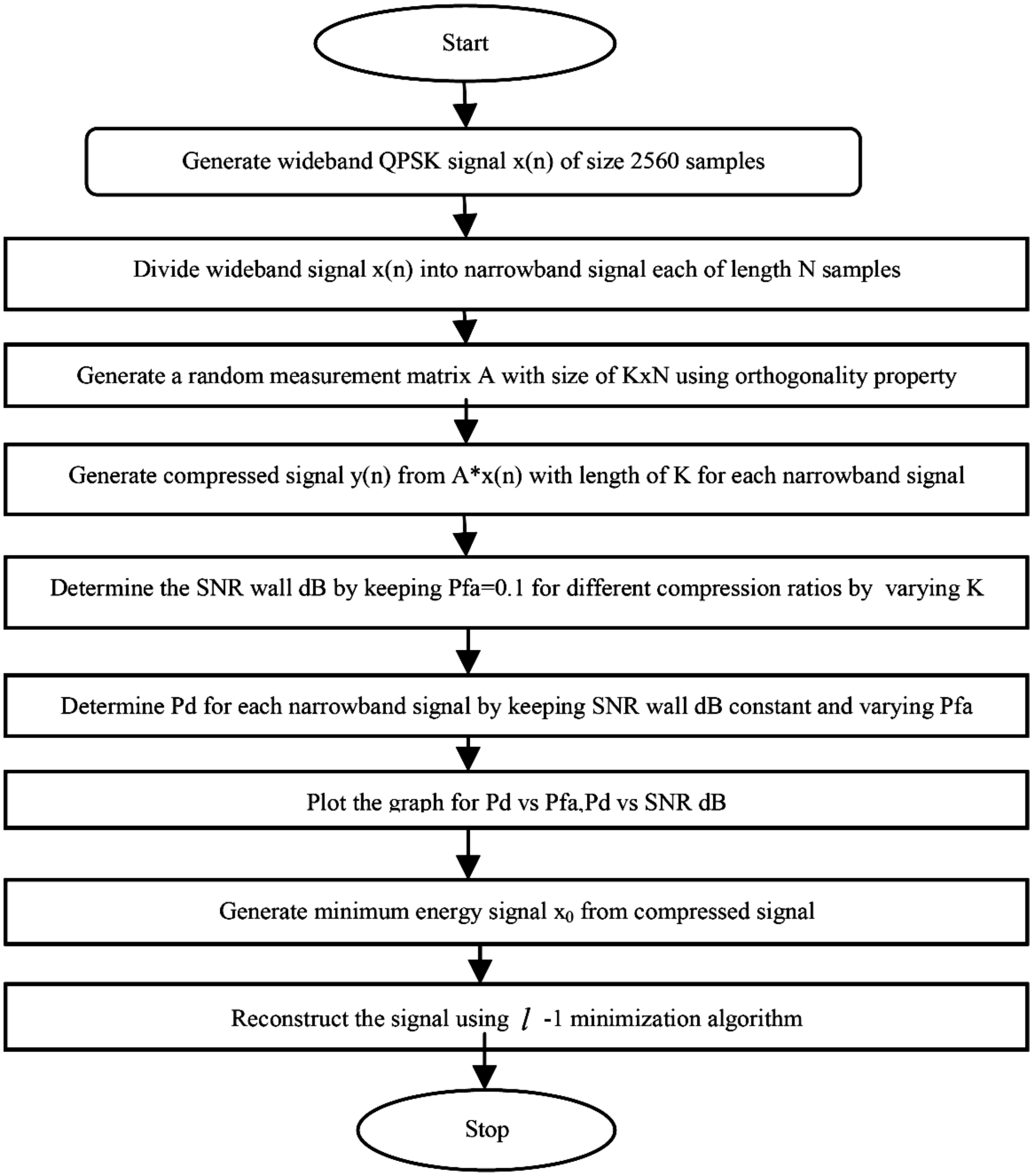

Figure 5: Flow chart

4. IMPLEMENTATION RESULTS AND DISCUSSION

The wideband Primary User signal used in simulation is QPSK signal with 2560 samples which is shown in Fig 6(*a*). Wideband channel is divided into five narrowband channels of each length 512 samples. The narrow band signal is 50% compressed by multiplying original signal with measurement matrix A of size K*N and minimum energy signal is obtained by multiplying transpose of A with the compressed signal which is shown in Fig. 6(*b*). Fig. 6(*c*) shows the reconstructed signal which is obtained from 50% compressed signal using *l*-1 minimization algorithm.

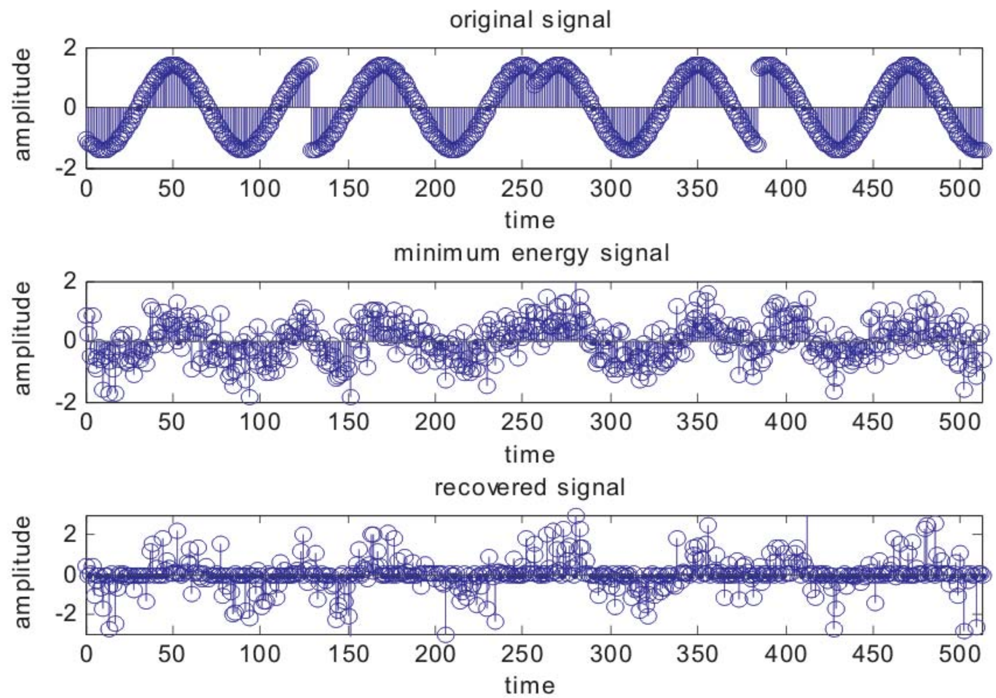

Figure 6(*a*): Received PU signal for single narrowband channel (*b*) Minimum energy signal (*c*) Recovery of Compressed QPSK signal with K = N = 50%

Fig.7 shows the Receiver Operating Characteristics (ROC) for observing the detection performance through Pd for each SNR value. In this paper the SNR is assumed to be between 0 and -14 dB. Here we are detecting SNR value with respect to Pd by keeping Pfa=0.1 as a constant for various compression rates. The detection performance Pd increases linearly with compression rate and even if the SNR is very low. So the system performance is increased with the proposed method.

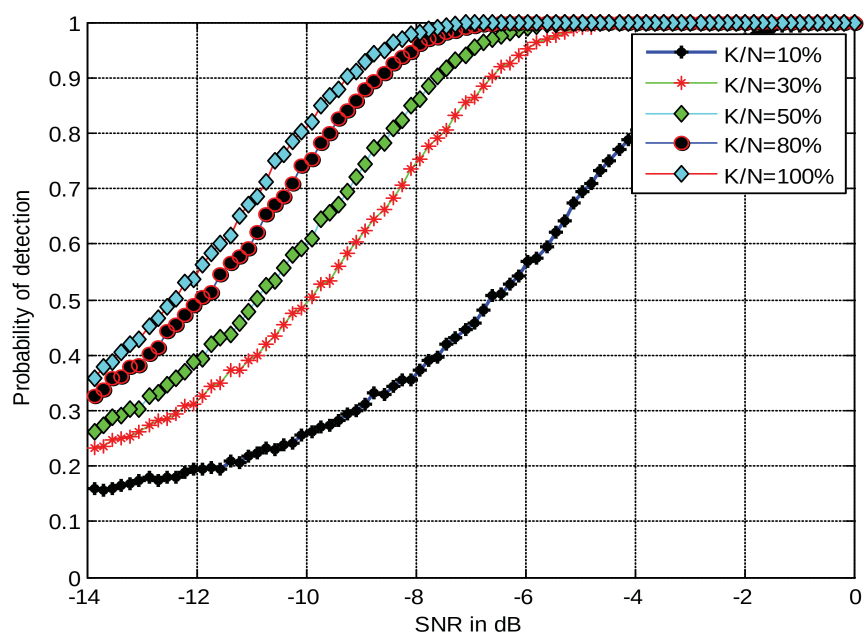

Figure 7: ROC curves of SNR verses P_d of proposed CSS technique for different compression Rates

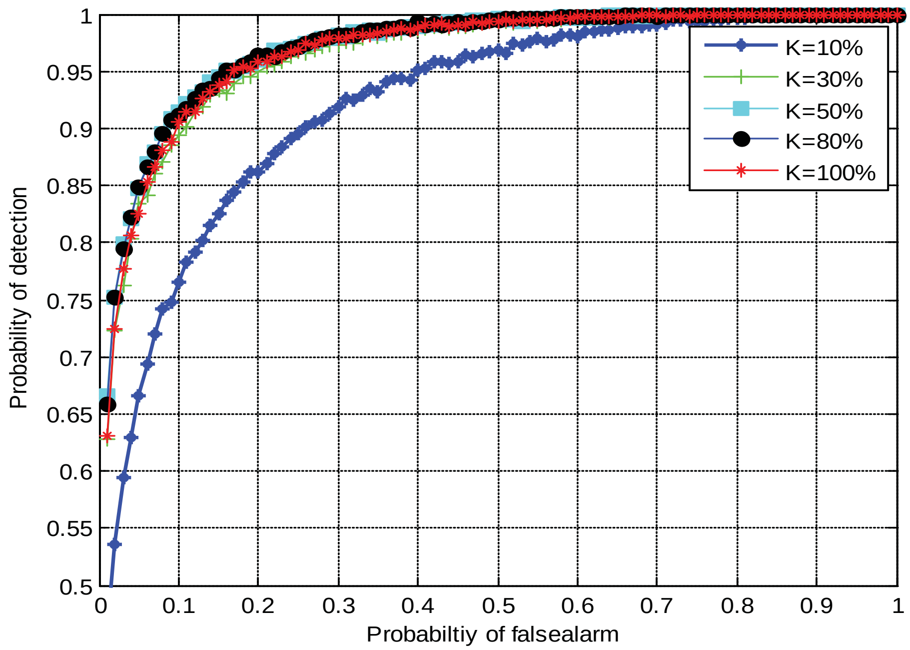

Figure 8: ROC of P_d and P_{fa} of proposed CSS technique for different compression rates

Table 2
Comparison of SNR Wall

Compression rate in %	*SNR wall*
10	–3dB
30	–6.6dB
50	–7.6dB
80	–8.5dB
100	–9.2dB

SNR wall dB for the different compression rates are shown in Table 2. The 10% compressed signal is identified at -3 dB, 30 % at -6.6 dB, 50 % at -7.6 dB, 80% at -8.5 dB and 100 % at -9.2 dB SNR respectively. But, the increase in the compression rate increments the number of samples that adds up the processing time. On an average, 50 % compression can be chosen to detect the PU signals at -7.6 dB which gains better performance than traditional Energy detection technique.

Fig. 8 shows the detection performance of P_d and P_{fa} for different compression rates by keeping the SNR constant. Pd increases linearly with compression rate ranging from 10% to 100%. P_d can be determined by using Monte – Carlo iterations. Monte-carlo iteration used to determine the performance matrices such as probability of detection are estimated for a given set of system tuning parameters by repeated trails with random realization on noise.

$$P_d = \text{(Number of detections)/ (Number of simulations)}.$$

5. CONCLUSION

In this paper the wideband QPSK signal is generated with a length of 2560 samples and compressed with a measurement matrix A of size KxN. Proposed work performs compression of a wideband signal and senses each narrowband channel using energy detection technique. In this work, a unique measurement matrix is produced to obtain minimum energy coefficients of the received signal. The minimum energy signal is then reconstructed using *l*-1minimization algorithm and the simulation results are discussed for different compression rates. Compressive sensing is extended for other sensing methods like matched filter, Cyclostationary detection etc., All simulations are carried out using MATLAB.

6. ACKNOWLEDGMENT

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