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# Design of Energy Detection based Multistage Sensing Technique

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***Abstract:*** **Most of the conventional spectrum sensing algorithms are based on cognition of transmitting signal features. The general approach for utilizing this cognition property is by bearing some information of the signal being transmitted. At the receiver end the detector obtains final decision explaining the existence of the signal in a certain specific spectrum band it utilizes for transmission. Moreover, in order to ameliorate the detection accuracy for a fixed value of false alarm probability is a dispute to maximum spectrum detection approaches. In this paper, we present a reliable optimal hybrid spectrum sensing scheme (ROHSS) based on energy detection for cognitive radio network. The proposed two stage ROHSS algorithm implements two detectors acting simultaneously corresponding to signals containing high and low signal to noise ratio. In first stage, an enhanced energy detector (EED) is used for the high Signal to noise ratio and an anti eigenvalue-based sensor detecting the signals with low signal to noise ratio. In second stage, student-teacher neural network (STNN) based sensor takes advantage of approximated eigen values of the transmitted signal and obtains a result regarding the existence of the signal. The main objective of the developed ROHSS algorithm is to detect the available frequency slots and allocated them to the cognitive users immediately in order to minimize the delay because of the efficient performance of the decision fusion method. The proposed ROHSS algorithm is analyzed and the performance is compared with the available sensing algorithms.**

***Index Terms: Cognitive Radio Network, Energy Detection, Signal-to-Noise ratio, STNN***

## I. INTRODUCTION

The Cognitive radios (CRs) exploit under-utilized transmission opportunities in licensed communication systems (Sharma & Joshi, 2018). A secondary user (SU) or the cognitive user can transmit in a frequency band only when no primary user (PU) is active in the band. To avoid collision with a PU, the cognitive user analyzes the band regularly for the availability of the spectrum bands (Juboori *et al.,* 2018; Pourgharehkan, Taherpour & Gazor, 2018). In each period, the SU performs sensing in a small portion of the time to sense the existence of any PU signal in the band (Tong *et al.*, 2018). If no PU signal is detected, the SU transmits in the band until the next sensing interval comes; otherwise, the SU stays silent. The detection accuracy in spectrum sensing is of critical importance for CR (Jun *et al.,* 2018). As per the detection strategy, the likelihood ratio test (LRT) is the most favorable detector. Many detection methods (Fouda, Hussain & Attia, 2018) have been developed so far to detect the available bands in the radio spectrum including energy detection, weighted energy detection, maximum-minimum eigenvalue (MME) detector, detector based on arithmetic to geometric mean (AGM), detection based on scaled largest eigenvalue (SLE), moment based detection (MBD), cyclo feature detection, autocorrelation, matched filter, covariance based detection (CBD), etc. Sensing based on energy detection (Gao *et al.,* 2018; Kumar *et al.*, 2018) calculates the average energy of the signal detected at secondary user by taking the average FFT of the N no. of samples and squaring its magnitude which is compared to a reference value predefined in order to find the existence of the signal. A blind robust eigenvalue based multi-antenna spectrum detection technique utilizes the likelihood ratio test (LRT) in order to improve sensing (Mehrabian & Zaimbashi, 2018). The correlation based detector (Chambers & sellathurai, 2018) calculates the auto correlation value of the no. of samples of the encountered signal taking the time-shifted values of the received samples at lag zero and lag one. Detection technique based on matched filter (Kabeel *et al.*, 2019) compares the characteristics of the received samples with previously determined and known pilots of the received PU signal. The cyclostationary detection (Alfi, Abdel-Atty & Mohamed, 2019) depends on the sampled set of examined values with the help of an analog to digital converter within the concerned band of frequency at Nyquist rate. A comparative study of energy based detector versus maximum minimum eigen value detector is done about the detection challenges and the detection accuracy with regard to the ROC (receiver operating

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characteristics) curves (Hamid, Bjorsell & Slimane, 2015). The following section of the paper describes the proposed hybrid detector design based on energy detection and explains its system model in section 2. Next section 3 explains the problem methodology and algorithm to implement the technique proposed. Operational analysis of the technique and comparative results are discussed in Section 4. At last, the conclusion drawn from the results is explained.

## II. Proposed Design

This paper focuses on developing a reliable optimal hybrid spectrum sensing algorithm (ROHSS) on the basis of energy based detection and eigen value based detection for cognitive radio network. Firstly, we used enhanced energy detector for high SNR and eigen value based detector used for low SNR. By selecting a path with the property of large channel gain from one end to another as well as large end-to-end signal to noise ratio generally, in order to represent the signal broadcast in between secondary source and secondary destination. The main purpose of developed ROHSS algorithm is to sense the free spectrum bands and allocates to primary user.

The System model of the developed multistage hybrid detection method is shown in figures below. The transmitter block is shown in figure 1, which consists of source signal which is encoded by an encoder followed by a modulator. The modulation technique implemented can be any one of the BPSK, QPSK or QAM. QAM is generally preferred for modulation as it is spectrum efficient. It can send more bits per sec in a given channel bandwidth as compared to other modulation techniques (Borkowski *et al.*, 2015). Finally, the signal is passed through IFFT block and transmitted through transmitting antenna.

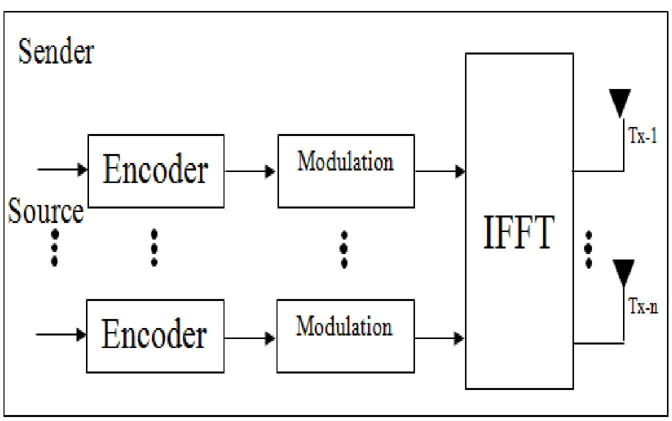


Figure 1: Transmitter Block

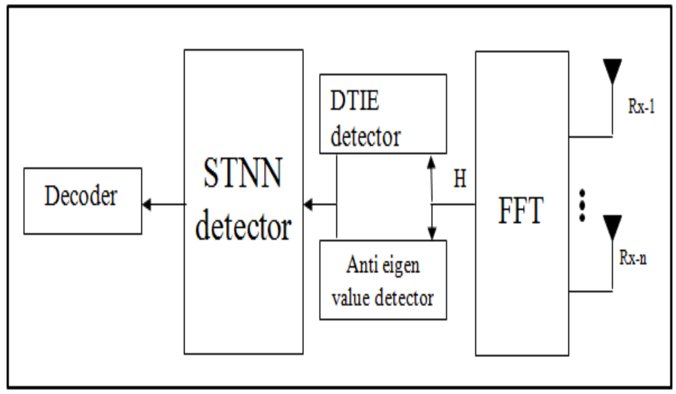


Figure 2: Receiver Block

At the receiver end the signal is received and undergo through FFT, followed by two parallel detectors EED (enhanced energy detector) and AEVD (Anti eigen value detector) on the basis of SNR estimation, the final decision is obtained from a STNN detector. At last, the signal is decoded to obtain the original signal.

The proposed two stage ROHSS algorithm implements two detectors simultaneously for low SNR values as well as high SNR values accordingly.

An enhanced energy detector is used for the signal with larger SNR and the signal with lesser SNR is analyzed by anti eigen value detector on the basis of their advantages and implementation issues. In second stage, student-teacher neural network (STNN) based sensor employs approximated eigen values of the received signal and obtain the conclusion in the confused state.

### A. *First Stage Detector*

Spectrum sensing is described as the central capability of cognitive radio to reset the functional arguments. It is used to distinguish the available frequency bands which are transmitting the data in quality of service. The available spectrum is identified from the displayed and concealed licensed user nodes. (Chen *et al.*, 2019). In order to reduce the operational abjection and the interference faced by the primary user in the band, 116 dBm is set as the sensitivity level by the 802.22 working group. This sensitivity level is used for identifying the existence of primary user if channel is idle. Thus the interference present in the band will be reduced. The interference is caused due to the unfortunate fading of cognitive radios. From the different research studies it is clear that spectrum usage in temporal and spatial domain is less because of the presence of 116dBm restrictions.

The above restriction allows a huge number of cognitive radios to be implemented which do not experience any adverse fading effect. The common challenge problem that the licensed or primary user identified is described by:

$$x(t)=\begin{cases} n(t), & H_0 \\ h.S(t)+n(t), & H_1 \end{cases} \quad (1)$$

The received signal by the cognitive radio is given by x(t), the broadcasting signal for the licensed user is indicated by S(t), n(t) indicate the AWGN, and h denotes the gain in the amplitude of the channel. $H_0$ is defined as the null hypothesis in case when the licensed user is absent in the channel. $H_1$ indicate the alternative hypothesis in which the licensed user is utilizing the channel for transmission. The sensing duration is increased in order to evaluate hypothesis more effectively. The detector will not work perfect when detector is working below the SNR wall value. The different types of detectors used are based on energy calculation, matched filter and on feature matching.

*B. Extracted Feature*

The proposed system is adopted with K number of secondary users and N number of sampling points in secondary user for a particular cognitive radio system. The PU signal is denoted by $H_0$ and if the PU signal is not present $H_1$ indicate that situation. This situation is modeled as:

$$x(t)=\begin{cases} n_i(t) & H_0\ i=1,2,..........K \\ S_i(t)+n_i(t) & H_1\ i=1,2,.........K \end{cases} \quad (2)$$

In the above equation S(t) represents the licensed user and the additive white Gaussian noise is given by $n_i(t)$, whose mean considered as 0 and the variance is denoted by $\sigma^2$. Let $S$=1 and $S$ = 0, accordingly, denotes the licensed user stage. Ideality of channel given by C is measured as:

$$C=\begin{cases} 0 & S=1, \\ 1 & S=0 \end{cases} \quad (3)$$

When C = 0 represents the spectrum cannot be utilized and C = 1 represents the availability of spectrum that can be used. The sample vector for $i^{th}$ SU user is given by $X = [x_i(1), x_i(2), . . . , x_i(N)]$. The sensing matrix that is derived from the above information is given by:

$$X=\begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(N) \\ x_2(1) & x_2(2) & \dots & x_3(N) \\ \vdots & \vdots & \ddots & \vdots \\ x_k(1) & x_k(2) & \cdots & x_k(N) \end{bmatrix} \quad (4)$$

The received signal y(t) is given by:

$$y(t)=X(t)+n(t) \quad (5)$$

In the above equation X (t) notify the broadcast signal and the unwanted Gaussian noise which is additive in nature is given by n(t) with zero mean and variance $\sigma_n^2$. The covariance matrix is given by $R(N) = (1/N)XT$. For the signal feature selection the MME, MSE and RMET are the methods used. If the feature is selected threshold value for derivation is identified. But the threshold accuracy problem is the major problem in this technique. Thus machine learning based clustering algorithm is implemented and also the two-dimensional feature is taken here.

We need to bring out the signal decomposition approach to get the two dimensional feature that is the IQ disintegration earlier than getting the value of the sampling matrix, it is depicted as:

$$X_i^I = Xi * \sin\left(\frac{2\pi f_c n}{f_s}\right)\ n=1,2,.........N \quad (6)$$

$$X_i^Q = Xi * \cos\left(\frac{2\pi f_c n}{f_s}\right)\ n=1,2,.........N \quad (7)$$

As a result of IQ disintegration, two different sampling matrices:

$$X^I=\begin{bmatrix} X_1^I(1) & X_1^I(2) & \cdots & X_1^I(N) \\ X_2^I(1) & X_2^I(2) & \dots & X_2^I(N) \\ \vdots & \vdots & \ddots & \vdots \\ X_m^I(1) & X_m^I(2) & \cdots & X_m^I(N) \end{bmatrix} \quad (8)$$

$$X^Q=\begin{bmatrix} X_1^Q(1) & X_1^Q(2) & \cdots & X_1^Q(N) \\ X_2^Q(1) & X_2^Q(2) & \dots & X_2^Q(N) \\ \vdots & \vdots & \ddots & \vdots \\ X_m^Q(1) & X_m^Q(2) & \cdots & X_m^Q(N) \end{bmatrix} \quad (9)$$

Therefore, we obtain the values of covariance matrices in the form of $R^I(N) = (1/N)(X^I)\ T$ and $R^Q(N) = (1/N)X^Q(X^Q)\ T$. Then we calculate the corresponding eigen values $T^1$ and $T^2$ corresponding to both the covariance matrix, now assume $T = [T^1, T^2]$ denotes property of the signal for the certain groups. The possibility of detection and false alarm probability in the proposed model is given by:

$$Q_f = P[H=1|H=0],$$

$$Q_d = P[H=0|H=1] \quad (10)$$

To calculate false alarm probability threshold value is needed.

The Tracy-Widom distribution is considered as an asymptotic distribution. This is used for focused and rescaled greatest eigen value of a matrix from the Gaussian Unitary Ensemble. Consider A and B are two independent matrixes. Consider the central Wishart matrices with p variables having mutual covariance along with some degree of freedom notified as m and n respectively. The dispersion of the greatest eigen value is given by $(A+B)^{-1}B$. Let us consider that there is a proportional increase in m and n with respect to p. As a result of focusing and grading, the dispersion becomes second order. By implementing the random matrix theory approach, we find the results for complex values first followed by the real valued data. The expression for second order Tracy-Widom distribution is given by:

$$F_2(s_0) = |(I - S_a)| \tag{11}$$

where $S_a$ reveals the Airy operator and I is the identity matrix.

### C. Student Teacher Neural Network Based Detector

Student-teacher coaching was initially utilized to examine the profundity in profound neural systems. At that point, this strategy was utilized to pack an enormous STNN to a smaller STNN which can be sent in gadgets with restricted computational and capacity assets. The term contains "information refining" and gave additional proof of the adequacy of the understudy instructor preparing calculation. As a rule, outline level cross entropy (CE) foundation is utilized for STNN preparing:

$$F_{CE} = -\sum_{t}\sum_{i=1}^{C} P^{ref}(i \mid X_t)\ \log(P^{model}(i \mid X_t)) \tag{12}$$

Where C is the all out quantity of setting subordinate (CD) HMM states and $P^{ref}\ (I \mid X_t)$ is the likelihood of highlight outline $X_t$ having a place with category I with respect to appropriation although $P^{model}\ (i \mid X_t)$ is the likelihood of highlight outline $X_t$ having a place with class I as indicated by the design prepared. In criteria for preparing, the address conveyance is derived from the constrained arrangement of the preparation information. All things considered, $P^{ref}\ (I \mid X_t)$ turns into a one-hot vector that is otherwise called preparing with hard names. The improved definition is given beneath:

$$F_{CE-soft} = -\sum_{t}\sum_{i=1}^{C} P^{teacher}(i \mid X_t)\ \log(P^{student}(i \mid X_t)) \tag{13}$$

The student architecture is checked especially to reduce the loss parameter as follows that is an interpellation among the soft and hard CE losses:

$$F = (1-\alpha)\ F_{CE} - Hard + \alpha F_{CE} - Soft \tag{14}$$

Where α represents the interpellation weight.

Right now, fuse understudy instructor preparing to evaluate FHL established for LSTMP AMs. We initiate with a good prepared LSTMP AM and afterward a FHL-adjusted STNN system is utilized as the instructor to apprise the FHL which is established for the LSTMP AM. We continue to fix every single other weight when evaluating the FHL bases. In this way, understudy instructor preparing is just used to gauge the FHL foundation. Besides, we don't introduce educator marks with the first hard targets. In this manner, we use,

$$P^{teacher} = P^{FHL-DNN} \tag{15}$$

$$P^{student} = P^{FHL-LSTMP} \tag{16}$$

Figure 3 shows the STNN architecture implemented where PM (primary memory), FM (Fitness Memory) and Mutation module are the main blocks. Registers i, j and r are for storage and input is in the form of $X_i$.

## III. Implementation of Proposed Design

The large SNR as well as the small SNR vlaues were detected using two different types of algorithms. The energy and eigenvalue is evaluated using student teacher neural network. The spectrum sensing is used to sense the free channel and allocate it to primary users, it reduces the transmission time in fusion center. In order to evaluate the ROHSS performance, a relative report was obtained between the ROHSS and three individual detection techniques, enhanced energy detector (EED), anti eigen value based detector (AEVD) and the student teacher neural network based detector (STNN). All the demonstrated graphs include the logical as well as the simulated outputs that are denoted with the help of lines and distinct numerical values, accordingly. Following algorithm illustrates the functional implementation of proposed ROHSS algorithm with two layer detectors.

Input x(t) is the received signal that is to be sensed and C denotes the existence of cognitive user. The received signal measures the input matrix to calculate the eigen values or the energy of the same is obtained to sense the spectrum. The Hypothesis gives the decision of the existence of the licensed signal in the band. If user is absent the band can be allocated to cognitive user else the primary user continues to transmit over its licensed band.

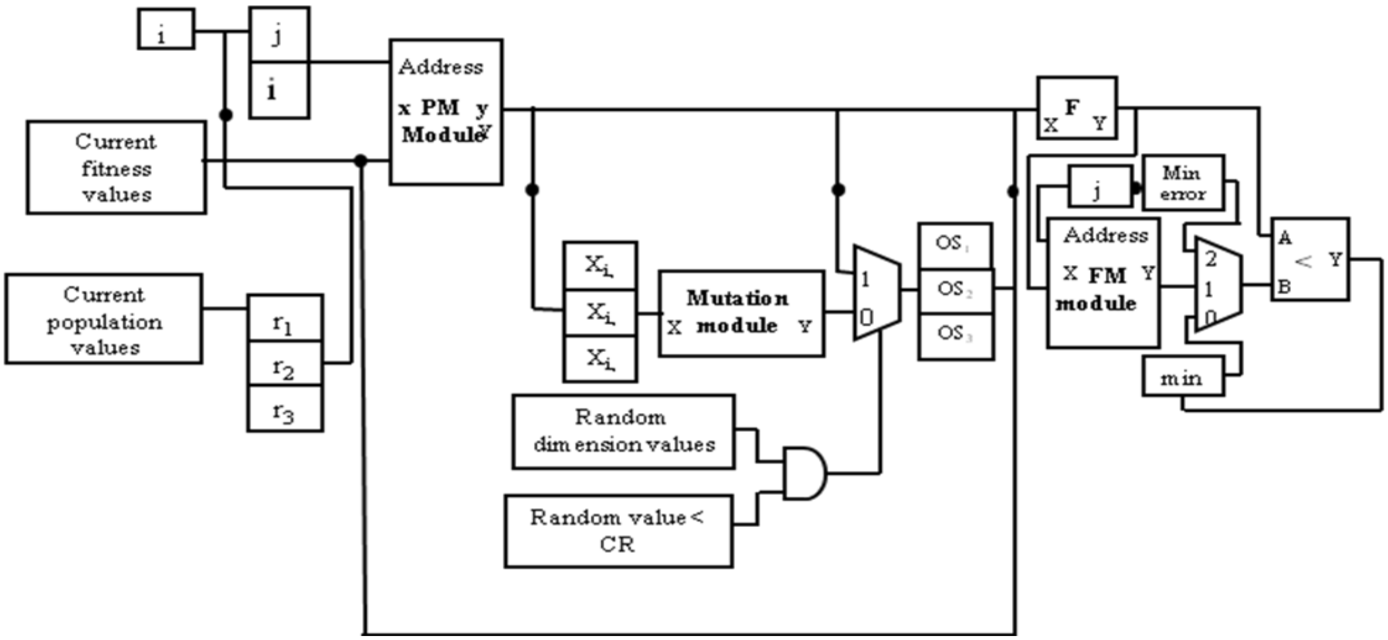


Figure 3: Student teacher neural network architecture

Algorithm 1: ROHSS for Spectrum Sensing

| | |
|---|---|
| Input | x(t), C, |
| Output | Spectrum Sensing |
| 1 | Initialize the input matrix, received signal. |
| 2 | Check for the user is in the given band |
| | $x(t) = \begin{cases} n_i(t) & H_0\ i = 1, 2, \ldots\ldots\ldots.K \\ S_i(t) + n_i(t) & H_1\ i = 1, 2, \ldots\ldots..K \end{cases}$ |
| 3 | if ($H_0$ == K ) |
| 4 | Calculate the $S_i(t)$ |
| 5 | Calculate the availability of C. |
| | $C = \begin{cases} 0 & S = 1, \\ 1 & S = 0 \end{cases}$ |
| 6 | Calculate total number of user in the band. |
| | Else |
| 7 | $H_i$, K= no user in the band. |
| 8 | end |

**Return** Spectrum Sensing

## IV. Results

The comparative analysis of individual detectors compared to that of combined detector is done in terms of bit error rate as depicted in figure 4. It depicts that the bit error rate of hybrid ROHSS detection technique is less as compared to individual detector acting alone under 64 QAM.

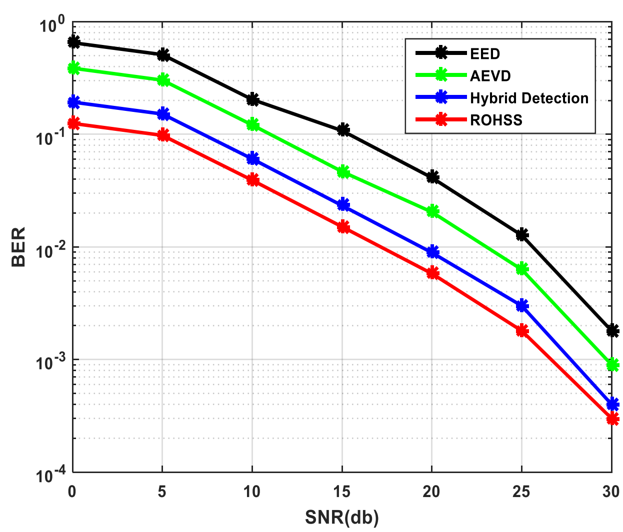


Figure 4: BER vs SNR for individual and Combined Detector under 64 QAM

It shows that BER of proposed ROHSS reduces with increase in SNR value and it performs better as compared to individual detectors acting alone at a certain SNR value ranging from 0dB to 30dB.

The complexity of operation in terms of number of nodes and number of floating point operation is plotted in figure 5 and 6 respectively.

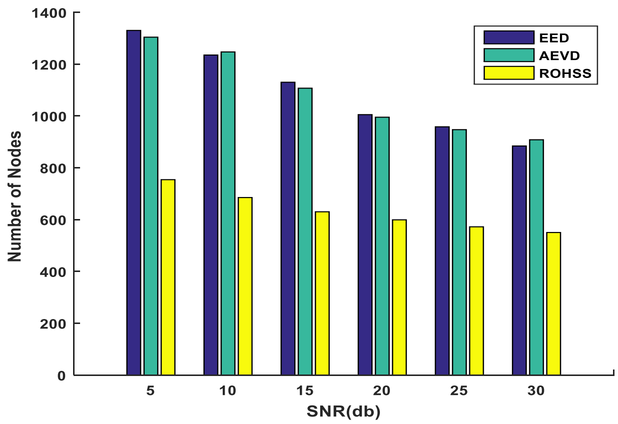


Figure 5: No. of nodes required for individual and combined detector vs SNR

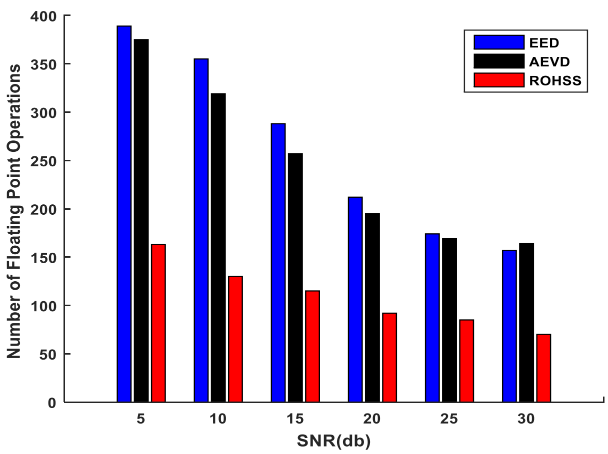


Figure 6: Complexity of individual and combined detector with respect to SNR

## CONCLUSION

A multistage hybrid spectrum sensing technique was developed named as ROHSS technique. It is a combined detector based on energy detection and eigen value detection. A student teacher neural network is implemented to reduce the sensing time. The bit error rate and system complexity is analyzed with the help of simulations which shows that the combined multistage ROHSS detector performs better as compared to the individual detectors implemented. The bit error rate is reduced as well as the complexity in terms of optimal number of nodes and optimal number of floating point operations required are also minimum in case of combined hybrid ROHSS detection technique.

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