SSRG International Journal of Mobile Computing and Application
ISSN: 2393–9141 / https://doi:10.14445/23939141/IJMCA-V11I1P101

Volume 11 Issue 1, 1-8, Jan-Apr 2024

Original Article

A Reliable Optimal Hybrid Spectrum Sensing Algorithm with Hardware Impairments for Cognitive Radio Network

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Received: 13 January 2024 Revised: 17 February 2024 Accepted: 04 March 2024 Published: 20 March 2024

Abstract *- Spectrum sensing algorithms exploit partial knowledge about the signal structure. A typical strategy for doing this is feature matching, i.e. having prior knowledge about some features of the signal; the detector makes a decision based on whether the feature is present in the input. Maximizing the detection probability for a provided false alarm rate is a hectic challenge for most of the spectral sensing methods. This paper presents a reliable, optimal hybrid spectrum sensing scheme (ROHSS) with hardware impairments for cognitive radio networks. The proposed two-stage ROHSS algorithm utilizes two detectors for low and high Signal Noise Ratio (SNR) bands. In the first stage, a double-threshold improved energy detector is used for the high SNR band and an anti eigen value-based detector is used for the low SNR band based on their merits and complexities. In the second stage, the Student-Teacher Neural Network (STNN) based detector utilizes the estimated energy and eigenvalue of the signal and gives a decision. The main objective of the proposed ROHSS algorithm is to sense the vacant frequency slots and allocate them to the Primary User's (PUs) quickly in order to reduce the delay caused by the efficient operation of the fusion center. The proposed ROHSS algorithm is implemented in both MATLAB and Xilinx simulation tools and the performance is compared with the existing state-of-art algorithms.***

Keywords *- Cognitive Radio Network, Cooperative Spectrum Sensing, Eigenvalue, Energy Detection, FPGA.*

1. Introduction

Cognitive Radios (CRs) exploit underutilized transmission bands in authorized correspondence frameworks [1] [2]. A Secondary User (SU) can transmit in a freely available band only when no Primary User (PU) is present in the band. To achieve minimum interference to the primary user, the SU occupies the band occasionally [3]. In every period, the SU performs sensing in a little bit of an opportunity to recognize the nearness of any PU signal in the band. On the off chance that no PU signal is recognized, the SU transmits in the band until the PU is detected; in any case, the SU remains quiet. The identification of exactness in spectrum sensing is of basic significance for CR [4]. As indicated by the detection hypothesis, the ideal identifier is the Likelihood Ratio Test (LRT). A few sensing procedures [5] have been proposed to detect the radio spectrum, including energy detection, eigen value-based, Maximum Minimum Eigenvalue (MME) detector, Arithmetic to Geometric Mean (AGM) detector, Scaled Largest Eigenvalue (SLE) detector, Minute Based Detector (MBD), cyclo stationary detection, Covariance Based Detector (CBD), and others. Energy Detection [6][7] figures the energy of the received N samples as the squared size of the FFT arrived at the midpoint of over these N samples and thinks about it to an edge to get the sensing choice.

An efficient eigenvalue-based multistage wire spectrum Sensing procedure uses the Likelihood Ratio Test (LRT) to create identifiers [8]. The autocorrelation-based detector [9] figures the relationship capacity of the received N samples with the time-dependent interpretation of these N samples at slack zero and slack one. Coordinated channel location [10] is a strategy that matches the received samples with some pre-gathered and spared pilots of a similar essential client signal stream. The cyclostationary recognition [11] depends on a lot of perceptions tested by a simple advanced converter at a Nyquist rate in the intrigued recurrence band. A correlation between energy and MME detectors is obtained concerning the sensing complexity and the sensing accuracy as far as the Receiver Operating Characteristic (ROC) bends [12].

One basic importance in the activity of SUs, regardless of whether they work in half duplex or full duplex mode, is spectrum sensing. As an outcome, a lot of effort was made in determining ideal, imperfect, specially appointed and helpful systems, just as investigating their spectrum sensing abilities [13]– [16]. The greater part of these works expected a perfect radio frequency (RF) frontend for the CR handsets. Nonetheless, pragmatic CR gadgets experience the ill effects of equipment flaws, for example, Low Noise Amplifier (LNA) non-linearity [17], neighborhood oscillator stage commotion [18], and in-stage (I) quadrature (Q) Imbalance (IQI) [19]. Especially, IQI relates to the adequacy and stage bungle between I and Q parts of the handset and, at last, prompts defective picture dismissal that acquires impressive presentation debasement [20]. In any case, the vast majority of them do not think about the impacts of equipment impedances, which can seriously corrupt the Cognitive Radio Networks (CRNs) technique.

This paper focuses on developing a Reliable Optimal Hybrid Spectrum Sensing (ROHSS) algorithm with hardware impairments for cognitive radio networks. Firstly, a double-threshold improved energy detector for a high signal-to-noise ratio is implemented, and an eigenvalue-based detector is used for a low signal-to-noise ratio simultaneously. The remaining part of the paper includes section 2, giving the literature overview to date. Section 3 describes the problem methodology and system model of the developed design. Section 4 provides the performance evaluation. At last, Section 5 concludes the paper.

2. Related Work

As Bkassiny et al. [21] exhibited an independent Cognitive Radio (CR) design, considered as the Radiobot. This model denotes past versatile radio frameworks to abuse the fundamental elements of discernment which, right now, essentially are self-learning and self-reconfiguration. With no earlier information on the RF condition, the Radiobot applies a grouping of progressively refined preparing steps to distinguish and recognize the detected signals. Specifically, here, it applies a visually impaired energy detection accompanied by a cyclostationary identification technique to recognize the dynamic signals and concentrate their fundamental intermittent characteristics as meditated in cyclic frequencies.

Le et al. [22] proposed a versatile MAC convention for full-duplex (FD) cognitive radio systems where FD cognitive users carry out channel dispute accompanied by simultaneous spectrum sensing and transmission, just with the most extreme force in two distinct stages in every conflict and admission cycle.

Patil et al. [23] introduced an extensive study of developmental accomplishments of eigenvalue-based spectrum sensing calculations. It utilized various combinations of eigenvalues to examine measurements as well as the circulation of eigenvalues and inference of probability of recognition following Random Matrix Theory (RMT).

Gao et al. [24] investigated the detection technique of eigen value based calculations encounters an immense decay when the received signals are uncorrelated. Along these lines, packed sensing is embraced to diminish the computational multifaceted nature and present the importance of numerous received signals. The calculated covariance matrix and its eigenvalues are determined under the non-reproduction structure of packed sensing.

Chen et al. [26] introduced a non-cooperative spectrum sensing for CRNs, which consolidates the multistage system, stage space reproduction technique and particular spectrum entropy strategy to detect the spectrum of narrowband remote signals. Reproduction results prove that this calculation can significantly improve the detection probability at a low Signal-to-Noise Ratio (SNR) (from −19 dB to −12 dB), and the detector can rapidly accomplish the best detection method as the SNR increments. This calculation could advance the improvement of CRN and the utilization of Wireless Sensor Networks (WSNs).

Awin et al. [27] displayed the spectrum sensing approaches that can be named visually impaired and information-helped approaches. This instructional exercise condenses blind spectrum sensing approaches that require no earlier information of the PU signal qualities, explicitly for an interlace CRN model. The instructional exercise gives an exhaustive foundation, significant usage, and constraints of the Blind Spectrum Sensing (BSS) methods.

Mu et al. [28] displayed a multistage sensing that propelled a warmed discussion because of its ability to exploit every detector. Propelled by this, an examination concerning multistage spectrum sensing is led. A two-stage spectrum detector is proposed dependent on energy detection and a Covariance Absolute Value (CAV) based detector here.

3. Research Methods

The Signal bandwidth effect on a detector is studied with respect to the comparison bandwidth. In the case of energy-based detection, the detection probability grows linearly as the signal bandwidth grows. In the case of the MME detector, the optimum measure of the ratio among the signal and observation bandwidth is evaluated as 0.5. On the basis of the inequality, a hybrid detector is proposed, combining two detectors. It accomplishes more detection accuracy as compared to individual sensing, and the implementation difficulty lies between the two individual detectors.

The proposed detection scheme is blind and self-adjustable on the basis of their SNR measurements. The detection accuracy is measured in terms of detection probabilities [29]. The dispersion of obtained eigenvalues gives an interesting research domain to solve cognitive radio challenges specifically for spectrum sensing [30].

As shown in Figure 1, assume a cognitive radio network that includes PU and Cognitive Radio (CR) devices that function in full duplex mode. Every cognitive user is considered a transceiver in which a signal is transmitted from the sender or transmitted to the receiver. High and low signal-to-noise ratio is detected using a Double Threshold Improved Energy (DTIE) detector and an anti-eigenvalue (AEV) based detector, respectively. Consider the interference among PU links is reduced by designing a suitable multiple access method. Further, both the single as well as multichannel detectors ignore the path loss among the transmitters and receivers for ease of calculations and simulations.

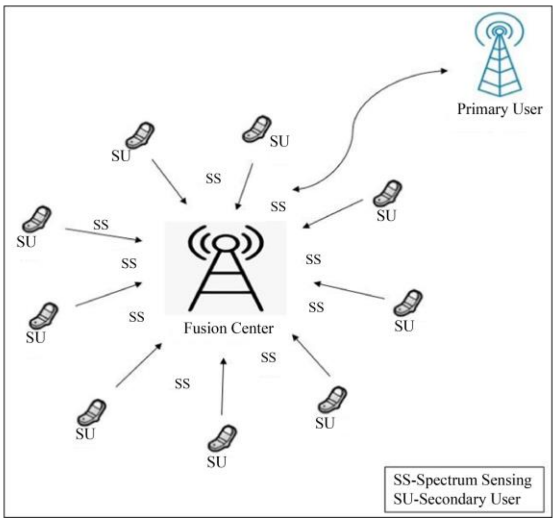

Fig. 1 System model for Proposed ROHSS technique for CRN

3.1. High SNR detection using (DTIE) algorithm

The regular energy detector has a single threshold value; the exact threshold which accomplishes the detection probabilities of false alarm and detection may not be precisely figured by utilizing limit choice procedures as a result of incorrect parameter estimations, e.g., noise estimation uncertainty. In this way, the chosen limit might be given as vulnerability. This limited vulnerability may altogether affect the normal identification technique. In the event that the limit vulnerability range can be reduced, solid choice can be normal from the energy Detector. This thought rouses the twofold limit energy detector. It turns into a twofold edge energy detection calculation with two predefined thresholds (V_{tho} and V_{th1}). The PU will be identified if and only if $V > V_{th1}$ and will not be detected if $V > V_{th0}$, relating to H1 and H0 individually.

Right now, threshold values V_{th0} and V_{th1} have been utilized to help the choice of the optional client. In case when the estimated energy surpasses V_{th1}, at that point, this client reports H1, which implies that it detects the primary user. In case the estimated energy is not exactly V_{th0}, choice H0 will be made. On the other hand, if the estimated energy is somewhere in the range of V_{th0} and V_{th1}, at that point, the PU's existence is additionally taken into consideration, and its observational energy is obtained. At the point when the distinguished energy V lies in between the two predefined thresholds (V_{th0}, V_{th1}), this outcome is invalid since it is anything but difficult to detect. From the proposed framework the presentation pointer for the detection probability, false alarm probability and missed detection probability for the twofold limit technique is determined utilizing.

$$P_0 = P\left(V' > \frac{V_{th1}}{H_1}\right) = Q_u\left(\sqrt{2\gamma'}, \sqrt{V_{th1}}\right) \tag{1}$$

$$P_U = P\left(V' > \frac{V_{th1}}{H_0}\right) = \frac{r\left(u, \frac{V_{th1}}{2}\right)}{r(u)} \tag{2}$$

$$P_b = P\left(V' \leq \frac{V_{th0}}{H_1}\right) = 1 - p_0 \tag{3}$$

Here, P_o is the likelihood perception when an essential client is available. P_u is the likelihood that the essential client is identified as present when, in actuality, it is absent. P_b is the likelihood according to which the licensed user may not be distinguished, when in real time environment it is available. As per our proposed Improved Double Threshold Energy Detector we are utilizing two limit esteems (V_{th0}, V_{th1}) in improved vitality indicator.

Here, by including the upside of less likelihood of crash of Double edge calculation with a bit of leeway of better Detection of Improved Energy identification of range detecting, better execution accomplished in the Energy location technique for range detecting. Conditions for discovery likelihood, pseudo caution, crash likelihood and range non-accessible likelihood are given as the pursuing equation that denotes the probability of collision.

$$P_c = P\left(V < \frac{V_{tho}}{H_0}\right) \tag{4}$$

The probability of the spectrum non-availability is obtained by the following equation.

$$P_c = P\left(V > \frac{V_{tho}}{H_0}\right) \tag{5}$$

Next equation represents the detection probabilities of the proposed model.

$$P_f = P\left(V > \frac{V_{th1}}{H_0}\right) \tag{6}$$

$$P_d = P\left(V > \frac{V_{th1}}{H_1}\right) \tag{7}$$

The above conditions (6 & 7) portray the articulation for the spectrum detection probability by the proposed twofold limit-based spectrum sensing in an intellectual radio system. The double threshold technique can expand the accessible degrees of opportunity. The double threshold-based energy detector performs better than the traditional energy detector in helpful spectrum sensing systems with an OR rule. This technique not only limits the overall system energy utilization at the location coordinate but additionally decreases the system traffic by staying away from reports from agreeable hubs with difficult choices.

3.2. Low SNR using (EV) based detection

Describe In a custom application, notwithstanding, the indicator must face the whole multifaceted nature of a genuine situation. There are a few parameters of the model that can never be known precisely. Rather they are just accessible as appraisals up to a limited accuracy. These vulnerabilities in the model lead as far as possible in the detection technique, which cannot be overwhelmed by expanding the sensing time, regardless of whether the quantity of samples keeps an eye on unendingness.

The SNR underneath which the detector will neglect to heartily recognize a signal under the model vulnerabilities being referred to is known as the SNR divider. The concept of antieigen value values can be understood by assuming a Hermitian matrix M of order PxP, an angle among the nonzero vector y to By is given by ϕ. So, there will be a maximum P number of eigen values and eigen vectors (Ew, Yw) such that $By_w = E_w y_w$. We know that eigenvalues are calculated by maximizing cos ϕ while anti-eigenvalues are evaluated by minimizing cos ϕ. In order to obtain antieigen value based detection, first, we evaluate the covariance matrix of the received signal with k number of samples.

$$\hat{R}_y = \frac{1}{k} Y Y^H \tag{8}$$

The antieigen values of $\hat{R}_y$ are expressed as

$$\hat{V}_k = \frac{2\sqrt{\hat{E}_w \hat{E}_{P-w+1}}}{\hat{E}_w + \hat{E}_{P-w+1}} \tag{9}$$

Where $\hat{E}_1 \geq \hat{E}_2 \geq \cdots \geq \hat{E}_P$ are the eigenvalues for the covariance matrix$\hat{R}_y$. Let us assume that Z eigen values distinguish the binary hypothesis A0 and A1. Therefore, the test statistic for AEVD will be the addition of the Z number of antieigen values given as

$$T = \sum_{w=1}^{Z} \hat{V}_k = \sum_{w=1}^{Z} \frac{2\sqrt{\hat{E}_w \hat{E}_{P-w+1}}}{\hat{E}_w + \hat{E}_{P-w+1}} \tag{10}$$

Where Z denotes the rank of the sample covariance matrix, which gives the optimum count of small antieigen values to obtain the test statistics, eigen esteem put together detectors depending with respect to the largest Eigen esteem for recognition, similar to the MME and the GLRT (Generalized Likelihood Ratio Test) detector, require a base SNR for detection to such an extent that the smallest anti-eigenvalue under H0 and H1.

3.3. Student Teacher Neural Network (STNN) Based Detector

Conventional student-teacher learning has been utilized to examine, the profundity of profound neural systems. At that point, this strategy was utilized to pack a large STNN to a small STNN which can be sent in gadgets with restricted computational and capacity assets. The term contains "information refining" and gives additional proof of the adequacy of the student-teacher learning calculation. As a rule, outline degree of cross-entropy (CE) foundation is utilized for STNN learning:

$$\mathrm{CE_f} = -\sum_{t}\sum_{i=1}^{q} \mathrm{P^{thres}}(i|S_t) \log\left(\mathrm{P^{mod}}(i|S_t)\right) \tag{11}$$

Universally, the learner (Student) is prepared to reduce the adopted performance drawback that will be an interjection among the soft as well as hard cross-entropy disadvantages:

$$C = (1 - y)\ CE_f - \text{Hard} + yCE_f - \text{Soft} \tag{12}$$

Where γ is the interjection weight

Right now, the incorporated trainer learner is preparing to approximate factorized hidden layer grounds for long short-term memory acoustic models (LSTM AMs). We initiate from a considerably prepared long shot term memory projection based acoustic systems; also a Factorized Hidden Layer (FHL) assumed STNN architecture is utilized as a trainer in order to approximate, factorized hidden layer grounds for long short term memory projection based acoustic systems.

In continuation every former weight is kept constant while evaluating the factorized hidden layer grounds. In this way, understudy instructor preparation is just used to approximate the FHL bases. Besides, we don't introduce educator marks with the first hard targets. In this manner, we use,

$$P^{\text{trainer}} = P^{\text{FHL-STNN}} \tag{13}$$

$$P^{\text{learner}} = P^{\text{FHL-LSTMP}} \tag{14}$$

During the FHL bases estimation in the above equation.

4. Results and Discussion

The received signals with large SNR and small SNR are detected using two different types of algorithms. The output from double threshold-based energy and anti-eigenvalue-based detectors is evaluated using student student-teacher neural network. All the plotted graphs comprise logical as well as computational outputs that are expressed by numerical values and curves accordingly. To evaluate ROHSS performance, a relative examination is obtained among the proposed ROHSS with respect to three existing hybrid detection methods, namely two-stage Energy MME

Combined detector (2EMC), Hybrid Detector (HD) and Intelligent Spectrum Sensing Scheme (I3S).

4.1. MATLAB Simulation Result

It is expected that the broadband signal comprises various frequency bands to detect the subsequent channel. The signal and the absolute guard band transfer speeds are thought to be the probability of detection = 1 and probability of false alarm = 10^{-3}, 10^{-2}, 10^{-1} and 10^{-0} individually, while the examining rate is picked to be equivalent to the data transmission of the remote signal. Additionally, the channel inhabitance process is thought to be Bernoulli appropriated with probability and free across channels, while the signal difference is equivalent for all channels. In the accompanying graphs, the quantitative outcomes appeared as nonstop curves, although markers represent the recreation outcomes. Also, the exhibition of traditional energy based detection having perfect RF frontend is utilized as a standard. To make the ROHSS a completely blind identifier, the noise energy limit utilized by the ED should be evaluated indiscriminately. This commotion energy is assessed in a time instance known as fine detection time, where the sensing arguments were balanced as well as adjusted. The effect due to noise level approximation exactness upon the energy detection technique is examined. Some estimation systems for the noise level are proposed. As will be clarified here, the MME is utilized to gauge the commotion energy and to sustain it back to the energy detector to make the ROHSS a completely visually impaired self-adjusted indicator.

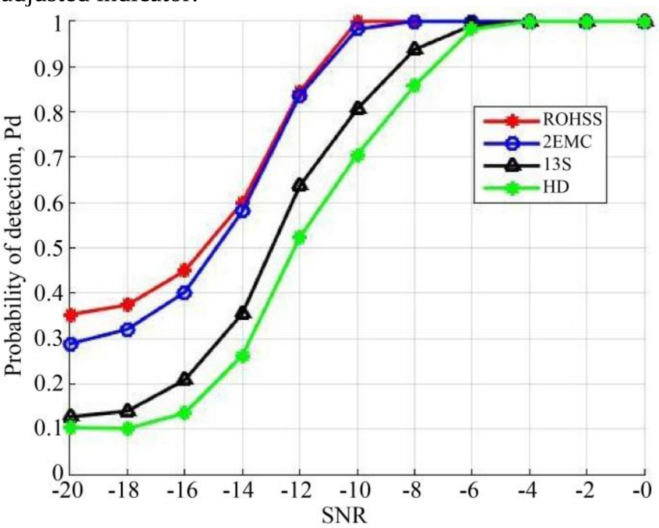

Fig. 2 Comparison of the probability of detection using existing and proposed technique

SNR	**Detection Accuracy (in %)**			
In (dB)	HD	I3S	2EMC	ROHSS
-10	70	80	98	100
-12	50	65	82	82
-14	25	35	58	60
-16	15	20	40	45
-18	10	15	32	38
-20	10	12	30	35

Figure 2 shows the effect of detection probability and signal-to-noise ratio. The non-linearity's on the exhibition of the traditional energy detector, expecting distinctive SNR values. In particular, in Figure 2, detection probabilities are plotted against the limit for various SNR values, thinking about P_d, SNR = - 20 dB and stage awkwardness.

It is apparent from Figure 2 that at low SNR values the proposed ROHSS technique gives better accuracy as compared to existing techniques. Furthermore, it is seen that for a fixed double threshold improved energy detector system, as SNR increases, the impedance for the neighbour and mirror channels increases; subsequently, the false alarm probability also increases.

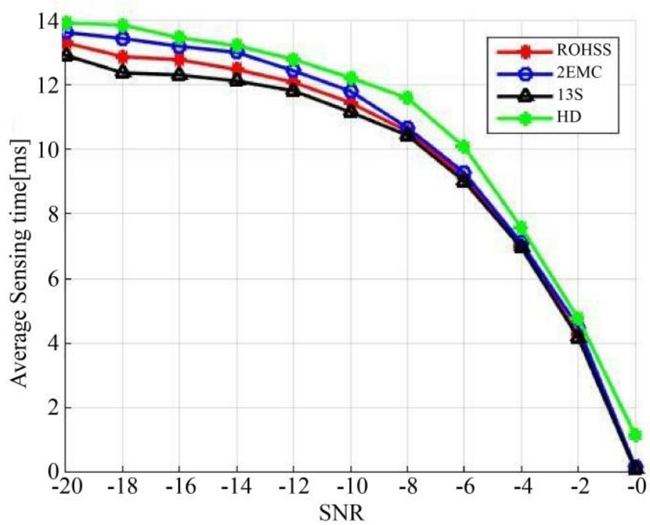

Fig. 3 Average time sensing comparison between existing and proposed

SNR	**Sensing Time (in ms)**			
In (dB)	HD	I3S	2EMC	ROHSS
-10	12.2	11.5	12	11
-12	12.5	11.8	12.4	12
-14	13	12	13	12.2
-16	13.5	12.2	13.2	12.8
-18	13.8	12.4	13.5	13
-20	14	13	13.8	13.2

Figure 3 depicts the sensing time vs SNR curves of comparison. Since there is a trade-off between detection accuracy and sensing time, the sensing time of the proposed ROHSS is slightly more than that of the Existing I3S technique. Such a slight increase in sensing time as compared to improved detection accuracy is worth it.

By performing energy detection from the start, the energy detector identifies the presence of a signal, at that point, a sufficiently high SNR is accepted, and signal presence is proclaimed. On the other hand, when the eigenvalue-based detection performs, at that point either a low SNR signal is available or just noise is received. To recognize those two conceivable outcomes, another phase of identification where low SNR signals can be distinguished is gone through.

This second phase of identification is MME, where higher probabilities of recognition for lower SNRs are accomplished at the cost of higher unpredictability. Fig. 4 represents the detection accuracy comparison among energy detector P_d^E, antieigen value-based detector P_d^M and combined detector P_d^C.

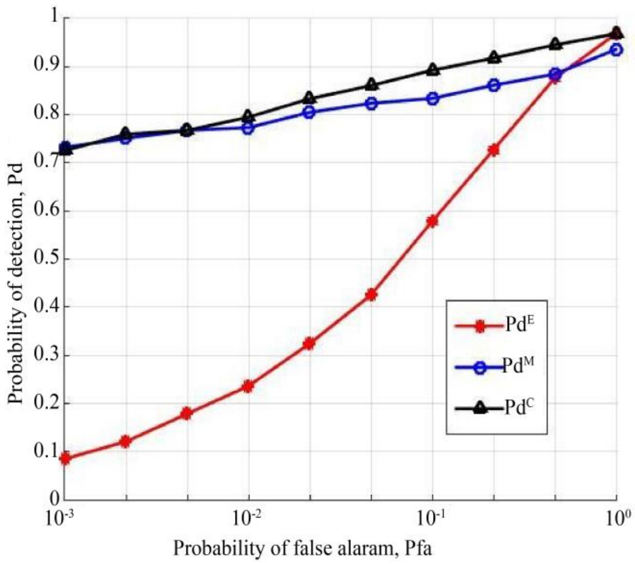

Fig. 4 Probability of detection vs probability of false alarm

Hence, it is very well expected that the detection accuracy of ROHSS's multifaceted nature can be dismissed. In ROHSS, the principal detector is an ED with a double threshold. At the point when signal energy is beneath the lower threshold, H0 is proclaimed, whereas H_1 is announced when the signal energy surpasses the upper limit. For signal energy in the middle of the two thresholds, the signal is passed to a second-organize recognition dependent on ROHSS calculation.

4.2. XILINX Simulation Results

FPGA design implementation of proposed ROHSS system. The proposed ROHSS technique was implemented on FPGA using Xilinx software. The design was encoded using verilog to obtain the simulation results as well as implementation results.

The performance of the proposed ROHSS is compared with existing architectures [26], [29], [30] in terms of performance metrics such as device utilization, maximum frequency, and power consumption of proposed and existing architectures. Table 1 shows the hardware utilization summary comparison between proposed and existing architectures [26], [29], [30].

Table 1. Hardware utilization comparison

Ref No.	FPGA family	Hardware utilization summary		
		Slice registers	Slice LUTs	Flip-flops
[26]	Virtex5	1254	989	432
	Virtex6	1387	967	698
[29]	Virtex5	1190	598	652
	Virtex6	933	784	1213
[30]	Virtex5	952	745	821
	Virtex6	1002	856	896
ROHSS	Virtex5	204	100	204
	Virtex6	260	148	140

For the proposed ROHSS architecture, Virtex5 instrument utilization in terms of LUT slice is denoted by 100, and slice register utilization is depicted by numerical value 204 utilization of flip-flops represented by numerical value 204. The Virtex6 FPGA utilization in terms of LUT slice is denoted by 148, slice register utilization is depicted by numerical value 260 utilization of flip-flops is represented by numerical value 140. The area utilization of the proposed ROHSS architecture is very low compared to existing architectures, i.e. 23%, 54% and 61% lower than the existing architectures [26], [29], [30] respectively. Table 2 shows the maximum operating frequency comparison between proposed and existing architectures [26], [29], [30]. It clearly shows the improvement of speed of the proposed architecture, which shows the highest frequency in virtex5 design as 416MHz. The speed of proposed ROHSS architecture is very high compared to existing architectures, i.e. 12%, 27% and 43% lower than the existing architectures [26], [29], [30] respectively.

Table 2. Maximum operating frequency comparison

Ref No.	FPGA family	Maximum operating frequency (MHz)
[26]	Virtex5	102
	Virtex6	98
[29]	Virtex5	198
	Virtex6	197
[30]	Virtex5	201
	Virtex6	276
ROHSS	Virtex5	416
	Virtex6	336

Table 3 shows the power consumption between proposed and existing architectures [26], [29], [30]. It clearly shows the reduction of energy utilization in the developed design by optimizing power consumption, which represents the effectiveness of the proposed architecture over existing architectures. The energy efficiency of the developed ROHSS system model is much less than that of traditional system models, i.e. 9%, 23% and 32% lower than the existing architectures [26], [29], [30] respectively.

Table 3. Power consumption comparison

Ref No.	FPGA family	Power consumption (W)
(26)	Virtex5	10.28
	Virtex6	18.97
(29)	Virtex5	9.45
	Virtex6	10.87
(30)	Virtex5	4.32
	Virtex6	5.23
ROHSS	Virtex5	0.324
	Virtex6	1.293

5. Conclusion

This paper researched the range-detecting execution of the ROHSS framework in both single-and multichannel vitality finders when the essential client gadgets utilize 2EMC methods and experience the ill effects of joint transmitter or collector. We inferred shut structure articulations for the bogus caution and identification probabilities under practical situations of non-flawless 2EMC and handset RF frontend debilitations, just as for the hypothetical situations of perfect RF frontend or potentially immaculate ROHSS. Our outcome delineated the debasing joint impacts of ROHSS and incomplete on the vitality locator range detecting execution, which brings about critical misfortunes in range use. In particular, on account of the single-channel vitality indicator, we saw that the free range detecting of the vitality edge might bring about a sensational increment of the bogus caution likelihood. In contrast, simultaneously, the discovery likelihood may altogether diminish.

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