



Cooperative Spectrum Sensing Architecture for Energy-Efficient Data-Fusion-Based Cognitive Radio Network

Premkumar S.^{1,*} D. Israel² S. Veerakumar¹ T. Praveenkumar¹

¹ Assistant Professor, Department of ECE, Knowledge Institute of Technology, Salem, Tamil Nadu, India

² PG Scholar, Department of ECE, Knowledge Institute of Technology, Salem, Tamil Nadu, India

Emails: spece@kiot.ac.in · svkece@kiot.ac.in

Received: November 02, 2024 Revised: December 21, 2024 Accepted: January 14, 2025 ★ Corresponding author

ABSTRACT

This demand can be satisfied by cognitive radio (CR) technology thanks to the growing desire to utilize existing radio frequency bands more effectively. This paper suggests a hardware-efficient, very-large spectrum sensor. In cooperative cognitive radio networks, data fusion is not provided by a new-scale integration (VLSI) architecture. The cooperative method to spectrum sensing and management as a proposed concept uses approaches for data fusion to address the difficulties. Our VLSI system delivers high throughput with exceptional performance by combining the latest sensing algorithms with an effective hardware architecture. The overall performance of the spectrum and spectrum awareness are enhanced by the cooperative theoretical radio communication system. In order to enable the network to make judgements that can be modified utilizing combined data from scattered spectrum sensors, the study examines the integration of network fusion techniques. The suggested scheme's primary characteristics are its hardware efficiency, low power consumption, and real-time flexibility for changing spectrum conditions. Through simulations and comparison with existing methods, it is assessed. System performance is tracked, and the results indicate that faster and more accurate spectrum sensing is required in order to apply notions of spectrum sharing that make sense.

Keywords: Cognitive radio ▪ Cooperative Cognitive Radio Networks ▪ Cooperative Spectrum Sensing ▪ Orthogonal Frequency Division Multiplexing

1. INTRODUCTION

The radio spectrum, a crucial and practical tool for wireless communication, is getting increasingly crowded as a result of the rising demand for records. The emergence of cognitive radio (CR) era offers a solution to this issue by enabling unlicensed users (also referred to as secondary users) to opportunistically access spectrum areas that are not being used by high consumers. Precisely identifying these empty regions is essential for making effective use of the spectrum, and it is a challenging task. Due to fading channels and noise, traditional spectrum sensing using male or female secondary consumers often has poor detection accuracy. Tasks in coop-

erative spectrum sensing (CSS) provide a potential solution. CSS increases detection precision and optimises spectrum utilisation by combining information from several secondary users. Nonetheless, human interactions and green information processing are essential for the implementation of CSS. This is where the cooperative spectrum sensors (CSRs') hardware-efficient VLSI designs software is located.

The development of data-fusion-based cooperative cognitive radio networks depends on the development of a hardware-efficient spectrum-sensor VLSI architecture. By maximising the use of the radio frequency spectrum, this novel VLSI architecture hopes to facilitate effective data fusion and coop-

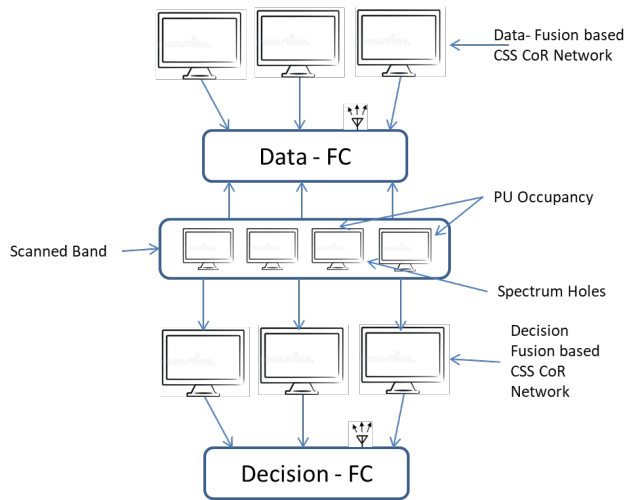


Figure 1. A Hardware-Efficient Spectrum-Sensor VLSI Architecture

erative communication amongst cognitive radio nodes. Data fusion is essential to cognitive radio networks because it makes network-level intelligent decision-making possible. Data fusion allows for collaborative spectrum management, dynamic spectrum access, and improved spectrum sensing by combining information from many sources and cognitive radio nodes.

Furthermore, cognitive radio networks can adapt to dynamic and heterogeneous settings by using data fusion techniques, which enhances spectrum efficiency and overall network performance. VLSI technology enables miniaturisation and optimised data flow, which is crucial for actual time spectrum detection in resource-constrained CR networks. Specifically, this work offers a novel hardware-efficient VLSI design for a CSR meant for data-fusion-based cooperative cognitive radio networks. Our architecture addresses the shortcomings of earlier systems with a data-fusion-based approach. By utilising efficient fusion techniques to merge data from numerous users, we are able to decrease computing complexity and maximise detection accuracy.

1.1 Problem Statement

Conventional CSS approaches are computationally demanding and hard to implement on low-resource devices. It is plausible that the existing VLSI architectures for spectrum sensors are not suited for data fusion or are unduly reliant on hardware. This has been taken into consideration, leading to the development of a hardware-friendly data fusion method that lowers computer complexity without compromising effective spectrum sensing performance. Provide a VLSI design for the Data Fusion Centre that is power, space, and processing performance efficient. It is important to optimize the chosen data fusion algorithm for this design.

1.2 Objective

The main objective of this study is to design a VLSI architecture that paves the way for small, low-power cognitive radio devices in CCRNs that have reliable spectrum sensing. This work's principal contributions are as follows:

- An innovative hardware-friendly algorithm that drastically lowers the computational complexity for coopera-

tive spectrum sensing.

- An effective hardware-efficient VLSI design that can accommodate up to six secondary users in the implementation of the algorithm.

2. LITERATURE SURVEY

Cooperative Spectrum Sensing (CSS) is a technique where multiple SUs collaborate to improve the accuracy of spectrum sensing by overcoming limitations like fading and hidden terminal problems. Existing systems for cooperative spectrum sensing architecture focus on data fusion and energy efficiency.

Rohit B. Chaurasiya et al. [1] offered a novel digital architecture based on maximum-minimum-eigenvalue (MME) for a spectrum sensor with a shorter sensing time and a lower critical-path latency. The proposed digital sensor was developed using 90 nm CMOS technology with an area of 0.42 mm². It operates at a maximum clock frequency of 404 MHz, which yields a 53.5 μ s sensing time. The architecture uses shared resources to significantly increase hardware efficiency, and hardware development was performed on an FPGA platform with real-time testing in a communication environment.

Rahul Shrestha et al. [2] proposed fast sensing-time and hardware-efficient eigenvalue-based blind spectrum sensors for cognitive radio networks. M. S. Murty and R. Shrestha [3] presented a reconfigurable and memory-efficient cyclostationary spectrum sensor for cognitive-radio wireless networks. K. Banović and A. C. Carusone [4] developed a sub-mW integrating mixer SAR spectrum sensor for portable cognitive radio applications.

Rahul S. et al. [5] offered a cooperative spectrum sensing area-efficient technique for data fusion-based cognitive radio networks. The recommended CSS algorithm outperformed the stand-alone spectrum sensing method by 9.45 dB at 0.5 detection probability with a false alarm rate of 0.1, according to performance analysis utilising 16-QAM modulation in a fading channel environment. It can accurately identify the primary user's spectrum occupancy by combining the signals received from six subordinate users. The CSR design was post-layout simulated in UMC 90 nm CMOS process and ASIC synthesised. At a maximum clock frequency of 101 MHz, it consumes 32 mW of total power, takes up 2.47 mm² of space, and provides an area-efficiency of 0.024 mm²/s.

Qingcheng Xiao et al. [6] executed various algorithms with different resource requirements and arithmetic complexity. They created hybrid, temporal, and spatial scheduling strategies, each with a different trade-off between throughput and delay. Nam-Seog Kim and J. M. Rabaey [7] presented a low-power wavelet-based energy detection spectrum sensor for the 3.1–10.6 GHz band. Vishal Khatri and G. Banerjee [8] created a broad spectrum sensing system for cognitive radio implemented in mixed-mode 130 nm CMOS technology. Tsung-Han Yu et al. [9] suggested a multitap-windowed frequency power detector with an adjustable threshold and sensing duration. Shridhar Mubaraq Mishra et al. [10] suggested a lightweight cooperative sensing approach grounded in hard decisions to lessen the sensitivity demands placed on individual radios.

3. PROPOSED METHODOLOGY

In order to find unoccupied spectrum bands (also known as spectrum gaps) that secondary users (SUs) can opportunistically access without interfering with primary users (PUs), Cognitive Radio Networks (CRNs) rely on spectrum sensing. Several SUs work together to overcome obstacles like fading and concealed terminal issues in order to increase the precision and dependability of spectrum sensing through a process called cooperative spectrum sensing (CSS). By merging information from many SUs, data fusion plays a critical function in CSS and helps make more reliable decisions about spectrum availability.

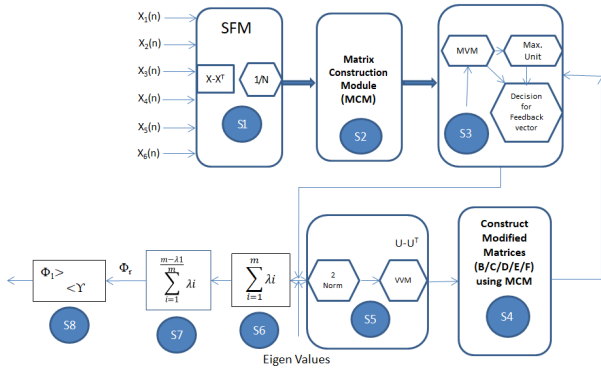


Figure 2. Proposed CSR architecture based on CSS algorithm

3.1 Joint Power and Subcarrier Allocation for Throughput Maximization

The optimisation problem can be simplified to the problem of jointly assigning subcarriers and power among all users in the network to achieve the maximum overall throughput, given the best power division scheme between eNB and RS for each subcarrier [12]. Simplifying the issue, we can say that it is:

$$\max_{P(d,e), \rho(d,e)} \sum_{d \in M} \sum_{e \in N} R(d,e) \quad (1)$$

The joint subchannel and power distribution approach is concluded by the algorithm in terms of maximising the total throughput. It has the following definition:

$$(x)^+ = \begin{cases} x, & x \geq 0, \\ 0, & x < 0. \end{cases} \quad (2)$$

It has been demonstrated that it is ideal via induction to allocate only one user with the best channel quality to each subchannel. The two objectives are ranked from most vital to least important, with the overall throughput being further maximised among feasible solutions and the fairness aim being the most crucial to optimum [13]. We apply the fairness definition, which states that maximum justice is achieved when each user has the same data rate. Maximum fairness can be attained by solving the max-min problem to maximise the rate that the poorest user can attain.

$$R_K = \sum_{e \in N} \rho(d,e) n \log(1 + H(d,e)P(d,e)) \quad (3)$$

3.2 Optimal Power and Subchannel Allocation

This lexicographic maximization problem can be solved by meeting the adequate condition described in the following theorem, which is met by the optimal joint power and subchannel allocation. Power allocation should still adhere to this technique in order to maximize throughput overall, as water-filling power allocation is always the optimum choice, regardless of subchannel assignment [14]. The water filling level, λ , is assumed to be determined by the channel gains on each subchannel. We may calculate the attainable rate for user k in the following way:

$$R_k = \frac{1}{n} \log(H(S_k^+) \lambda(S_k^+)) \quad (4)$$

$$\frac{H(S_k^+)}{\lambda(S_k^+)} \quad (5)$$

Thus, if this expression is balanced to produce the same value for every user $k \in M$, that is the optimal scenario. However, because of the computational complexity, it is very difficult to jointly distribute subchannels and power, since λ is a function of all channel gains, which will be decided by the subchannel assignment. Rather, the joint allocation is divided into two parts by the majority of unsatisfactory solutions to the comparable problem. Subchannels are first assigned with the assumption that transmission power is dispersed equally among all subchannels. After that, power distribution is optimised in accordance with water-filling based on the subchannel allocation.

3.3 Suboptimal Power and Subchannel Allocation

The suboptimal resource allocation system also consists of two steps. First, assuming that powers are distributed with a water-filling level of λ , we distribute subchannels among all users. Subchannel allocation from the first stage can then be utilised in the second step to calculate λ .

3.3.1 Suboptimal Subchannel Allocation Algorithm

The subchannel allocation mechanism is the sole topic of the first stage. Two new sets are introduced first, and then the subchannel allocation mechanism is suggested. Assume that after allocation, N_s is the subchannel set that remains. Initially, $N_t = N$. Define M_s as an ordered set containing all users $1, 2, \dots, m$ where for any $i, j \in M_t$, $i < j$ if and only if $H(S_a) \leq H(S_b)$.

1. Initialize: $S_x = \emptyset$, $H(S_x) = 1$ for all users $X = 1, 2, \dots, m$. Let $N_t = N$ and $M_t = M$.
2. While $N_s \neq \emptyset$, for $M_t(1), \dots, M_t(m)$, find a subchannel $l(x) \in N_s$ satisfying $H(d, e(l)) \geq H(d, e')$ for all $l' \in N_s$. Assign $l(x)$ to user x . Update $N_t = N_t - \{l(x)\}$ and $H(S_x) = H(S_x)H(d, e(l))$.
3. Reorder the user set M_t . Then go back to Step 2.

3.3.2 Optimal Power Allocation

Assume that each subchannel has a channel gain coefficient of $H(d, e)$ after the subchannels have been allocated based on the algorithm. According to the optimal water-filling power distribution, each subchannel receives a power that is equal

to

$$P_{d,e} = \left(\lambda - \frac{1}{H_{d,e}} \right)^+ \quad (6)$$

and λ is chosen to satisfy the total power constraint

$$\sum_{d,e} P_{d,e} = P_{\text{total}}. \quad (7)$$

4. MIMO PROCESS

Multiple Input Multiple Output (MIMO) is among the various types of multiple antenna techniques that are currently available and intended to greatly improve communication performance. Due to its ability to increase data speeds while preserving spectral efficiency, MIMO is particularly appealing in wireless communication because of the high multipath conditions in which devices operate [15]. Wireless protocols including WLAN 802.11n, IEEE 802.16, and 3GPP Long Term Evolution (LTE) have recently incorporated it or are considering using it. MIMO technique is expected to be used by all upcoming 4G wireless communication technologies.

Three general categories of multiple antenna approaches include spatial multiplexing, spatial diversity, and beam shaping. The use of spatial multiplexing is seen in MIMO systems. In rich scattering settings, multiple data streams are simultaneously supplied over many antennas to maximise the effective data rate. A minimum of two transmitters and two receivers are needed for MIMO spatial multiplexing, and the receivers must be in the same location. Due to the transmitters' independence, two mobile devices can be utilised in tandem for MIMO in the uplink. Here, the base station needs to synchronise the broadcasts, which means lining up the mobile devices' power and time. For regular cellular function, this process is essential.

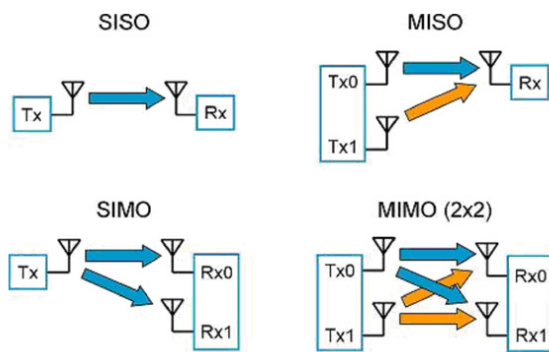


Figure 3. Channel configurations for SISO, SIMO, MISO, and MIMO (2x2) systems.

Two distinct transmit channels are shared by two antennas at the transmitter, and two distinct receive channels are shared by two antennas at the receiver. Combining multiple antenna pairs can also result in a multitude of additional MIMO combinations, such as 3x3 and 4x4. For a MIMO system, it is possible to design even an unequal number of antennas at the transmitter and receiver, or a $M \times N$ scenario in which M transmit antennas and N receive antennas are not equal.

Cooperative MIMO is a wireless communication system that uses the spatial diversity of numerous radio devices to produce distributed antenna performance. It is also known as virtual antenna arrays, distributed MIMO, network MIMO, or

virtual MIMO. There are multiple segments to the data stream that has to be sent. Each stream is thereafter sent out from a different virtual array device. Due to the devices' spatial separation from one another, the transmitted signals undergo a range of fading conditions, increasing signal variety and decreasing the consequences of signal interference. All of the devices' received signals are combined and processed collectively at the receiver side in order to recover the original data.

5. SYSTEM COMPONENTS

Cognitive Radio Networks (CRNs): These are wireless networks that allow devices to identify and utilise unused radio frequencies. As a result, the spectrum can be used more effectively than it could be under traditional static allocation.

Cooperative Spectrum Sensing (CSS): In CRNs, many cognitive radios can cooperate to improve the accuracy of spectrum sensing. This is due to the possibility that certain radios' detecting power is limited by noise or impediments.

Data Fusion: This is the process for combining information from various sources to create an image that is more accurate. Data fusion techniques are used to aggregate sensor data from many cognitive radios in order to determine the availability of spectrum in CSS.

VLSI Architecture: This article refers to the design of ICs, which are integrated circuits with a very high transistor density. The key objective here is to create an efficient hardware architecture for the spectrum sensor in terms of both space usage and power consumption.

SFM Matrix Construction Module (MCM): This block most likely represents the main module in charge of building a particular matrix that the image processing algorithm uses. Coefficients or weights that are utilised in computations throughout the process may be stored in this matrix.

Input Image: The raw image data that was taken by the camera sensor of the device is represented by this block.

Nine-1 Iterations: According to this section, the system should go through nine iterations of a certain image processing operation. The lines 4–13 that are mentioned may refer to certain lines of code in the method that has been put into practice.

Eigenvalue: The eigenvalues of a square matrix are numerical qualities, and this block most likely relates to calculating them. Eigenvalues are employed in dimensionality reduction and feature extraction, among other image processing applications.

Construct Modified Matrices (B/C/D/E/F) Using MCM: In this case, several modified matrices (B, C, D, E, and F) that are probably going to be employed in later calculations can be created using the SFM Matrix Construction Module (MCM) from block 1.

S4: Without more context, it is difficult to understand this block's goal. It could stand for a variable or intermediate step utilised during the nine rounds.

Deflation Technique: The use of a deflation technique is indicated by this block. Deflation techniques are used in linear algebra to make eigenvalue and eigenvector calculations simpler.

Output Image: Following the algorithm’s completion, this block displays the final processed image.

Overall, the block diagram suggests an image processing system that utilizes a specific matrix construction module (MCM) and performs calculations involving eigenvalues and potentially deflation techniques. However, without further information about the specific algorithm and the purpose of each matrix, a more detailed explanation of each step is not possible. In this proposed system in Table 1, the area, power consumption and sensing time obtained are shown below.

Table 1. Comparative Analysis with Related Works

Title & Year	Algorithm	Area (mm ²)	Power (mW)	Sensing Time (ms)
Cooperative Spectrum Sensing Architecture for Energy Efficient Data-Fusion Based Cognitive Radio Network (This paper)	CSR for data fusion-based CSS CRN	2.51	30.47	0.0421
Hardware-Efficient and Fast Sensing-Time Maximum-Minimum-Eigenvalue-Based Spectrum Sensor for Cognitive Radio Network [1] (2019)	Maximum-Minimum-Eigenvalue-Based Spectrum Sensor (MME)	0.42	38.24	0.0535
Fast Sensing-Time and Hardware-Efficient Eigenvalue-Based Blind Spectrum Sensors for Cognitive Radio Network [2] (2020)	Eigenvalue-Based Blind Spectrum Sensors	0.3742	33.07	0.0443
Area-Efficient and Scalable Data-Fusion based Cooperative Spectrum Sensor for Cognitive Radio [5] (2020)	GLRT based on Cooperative Spectrum Sensor	2.47	31.84	0.0610

6. RESULTS AND CONCLUSION

With cognitive radio, devices can search the radio spectrum for available frequencies in order to communicate wirelessly. They can thus coexist peacefully and without causing any issues with permitted users. This paper is devoted to the data fusion part of cooperative cognitive radio networks. In these networks, many radios collaborate to improve spectrum sensing accuracy. This design prioritizes less space and power usage without sacrificing its ability to effectively identify underutilized frequencies.

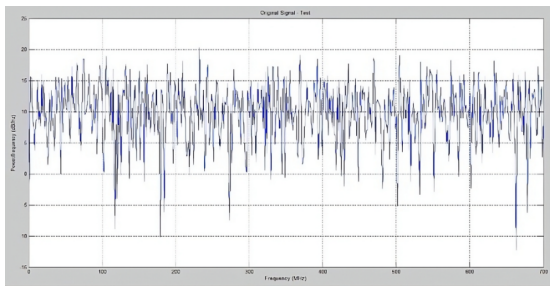


Figure 4. Original Signal Test

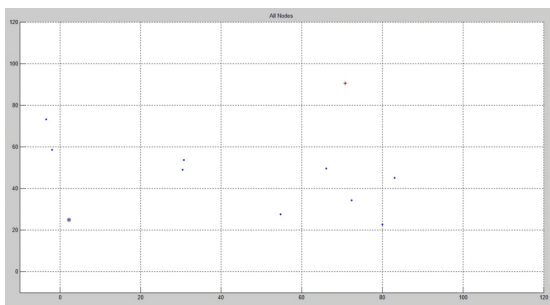


Figure 5. Multiple Nodes (Signal Towers)

7. CONCLUSION AND FUTURE SCOPE

This research proposes a novel hardware-efficient VLSI architecture based on data fusion for cooperative cognitive radio

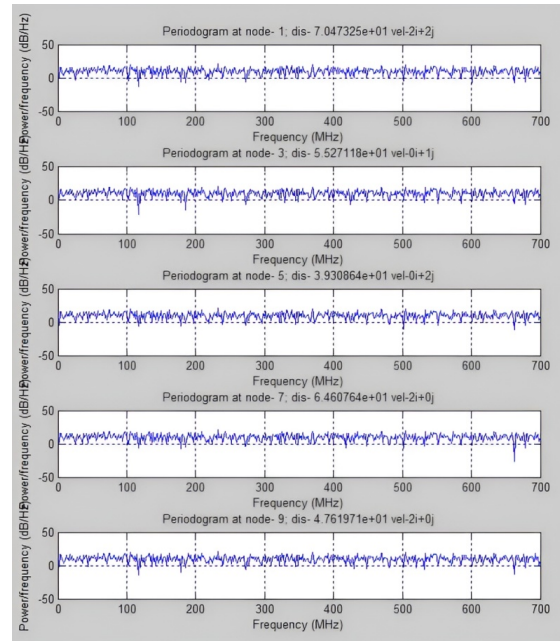


Figure 6. Periodogram for odd nodes

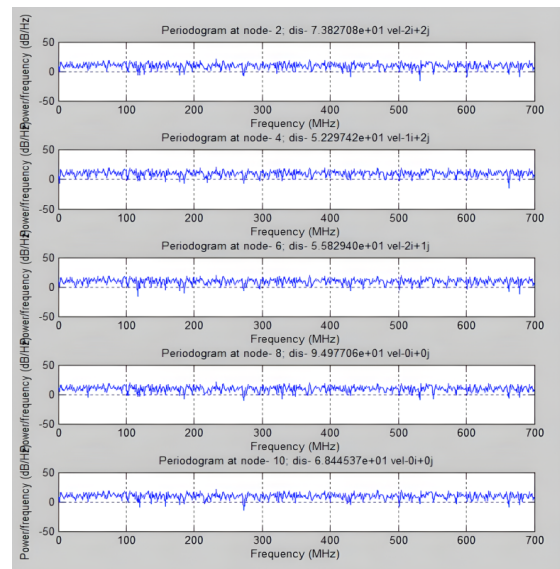


Figure 7. Periodogram for even nodes

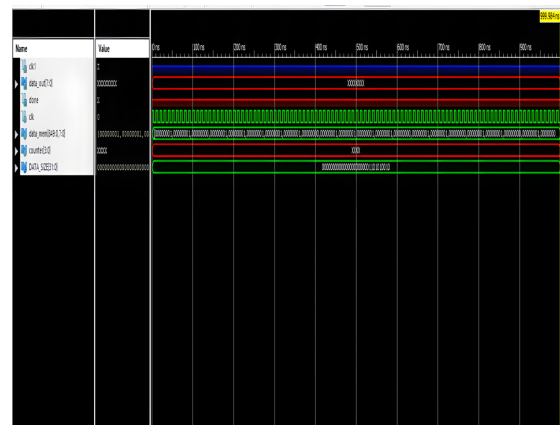


Figure 8. CCRN Data signal

networks (CCRN). In summary, cognitive radio is a wireless communication technique that enables devices to look for open frequencies in the radio spectrum. The design increases overall spectrum utilisation by facilitating effective collaboration among cognitive radio nodes to detect and access vacant spectrum bands more efficiently. By combining data from several nodes, spectrum sensing accuracy is increased and the chance of interfering with authorised users is decreased. The suggested architecture reduces chip size and power consumption by optimising resource utilisation inside the VLSI circuits. It is simple to adjust the modular design to various network setups and sizes.

Future advances in a few areas could benefit from this cognitive radio network design for spectrum sensing. First, the current architecture can only support a certain number of secondary users; future architecture may be expanded to accommodate a larger network, enabling more efficient use of the available spectrum. Second, the architecture is reliant on a specific data fusion technique; further research could explore sophisticated algorithms to augment spectrum sensing accuracy while maintaining hardware efficacy. Third, this VLSI design might be used with reconfigurable hardware, like FPGAs, to introduce adaptability, allowing the system to adjust to different sensing situations without needing to be completely redesigned.

REFERENCES

- [1] R. B. Chaurasiya and R. Shrestha, "Hardware-Efficient and Fast Sensing-Time Maximum-Minimum-Eigenvalue-Based Spectrum Sensor for Cognitive Radio Network," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 66, no. 11, pp. 4448–4461, Nov. 2019.
- [2] R. Shrestha and R. B. Chaurasiya, "Fast Sensing-Time and Hardware-Efficient Eigenvalue-Based Blind Spectrum Sensors for Cognitive Radio Network," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 67, no. 4, pp. 1296–1308, Apr. 2020.
- [3] M. S. Murty and R. Shrestha, "Reconfigurable and Memory-Efficient Cyclostationary Spectrum Sensor for Cognitive-Radio Wireless Networks," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 65, no. 8, pp. 1039–1043, Aug. 2018.
- [4] K. Banović and A. C. Carusone, "A Sub-mW Integrating Mixer SAR Spectrum Sensor for Portable Cognitive Radio Applications," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 65, no. 3, pp. 1110–1119, Mar. 2018.
- [5] R. B. Chaurasiya and R. Shrestha, "Area-Efficient and Scalable Data-Fusion Based Cooperative Spectrum Sensor for Cognitive Radio," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 68, no. 4, pp. 1198–1202, Apr. 2021.
- [6] Q. Xiao, L. Lu, J. Xie and Y. Liang, "FCNNLib: An Efficient and Flexible Convolution Algorithm Library on FPGAs," in *2020 57th ACM/IEEE Design Automation Conference (DAC)*, San Francisco, CA, USA, pp. 1–6, 2020.
- [7] N.-S. Kim and J. M. Rabaey, "A Dual-Resolution Wavelet-Based Energy Detection Spectrum Sensing for UWB-Based Cognitive Radios," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 65, no. 7, pp. 2279–2292, Jul. 2018.
- [8] V. Khatri and G. Banerjee, "A 0.25–3.25-GHz Wideband CMOS-RF Spectrum Sensor for Narrowband Energy Detection," *IEEE Transactions on Very Large-Scale Integration (VLSI) Systems*, vol. 24, no. 9, pp. 2887–2898, Sept. 2016.
- [9] T.-H. Yu, O. Sekkat, S. Rodriguez-Parera, D. Markovic, and D. Cabric, "A wideband spectrum-sensing processor with adaptive detection threshold and sensing time," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 58, no. 11, pp. 2765–2775, Nov. 2011.
- [10] S. Mishra, A. Sahai, and R. Brodersen, "Cooperative sensing among cognitive radios," in *Proc. IEEE International Conference on Communications*, vol. 4, pp. 1658–1663, Jun. 2006.
- [11] I. Nevat, G. W. Peters and I. B. Collings, "Distributed Detection in Sensor Networks Over Fading Channels with Multiple Antennas at the Fusion Centre," *IEEE Transactions on Signal Processing*, vol. 62, no. 3, pp. 671–683, Feb. 2014.
- [12] R. C. D. V. Bomfim and R. A. A. de Souza, "Performance of centralized data-fusion cooperative eigenvalue-based spectrum sensing under correlated shadowed fading," in *2015 International Workshop on Telecommunications (IWT)*, Santa Rita do Sapucaí, Brazil, pp. 1–6, 2015.
- [13] K. Baskar, K. Muthumanickam, P. Vijayalakshmi and S. Kumarganesh, "A Strong Password Manager Using Multiple Encryption Techniques," *Journal of The Institution of Engineers (India): Series B*, pp. 1–8, 2024, doi: 10.1007/s40031-024-01144-6.
- [14] K. Saravanan, S. Anthoniraj, S. Kumarganesh, T. Senthil Kumar and M. K. Sagayam, "Power Adjustment Algorithm for Higher Throughput in Mobile Ad hoc Networks," *International Conference of Computer Sciences and Renewable Energies 2021 (ICC-SRE 2021)*, Agadir, Morocco, Jul. 23–24, 2021, doi: 10.1051/e3sconf/202129701064.
- [15] N. Sugirtham, R. S. Jenny, B. Thiyaneswaran, S. Kumarganesh, et al., "Modified Playfair for Text File Encryption and Meticulous Decryption with Arbitrary Fillers by Septenary Quadrate Pattern," *International Journal of Networked and Distributed Computing*, vol. 12, pp. 108–118, 2024, doi: 10.1007/s44227-023-00019-4.