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SPECTRUM SENSING ALGORITHMS FOR COGNITIVE RADIO-BASED DISASTER RESPONSE NETWORKS, POTENTIALS AND CHALLENGES.

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Abstract

Spectrum utilization has remained an issue in the era of telecommunication due to the exponential and rapid growth in spectrum based mobile telecommunication technologies and advancements resulting in a huge demand on spectrum while spectrum utilization is restricted and under-utilized, the arrival of Cognitive Radio CR technology could make an important break-through towards resolving this issue, its functionality enables it to resolve the problem of spectrum shortage by enabling dynamic spectrum access feature, the issue of spectrum under-utilization is made more complicated in constrained networks such as public-safety, emergency and disaster response networks, where the need for deploying a reliable communication system is extremely high, these systems require sophisticated techniques to explore and utilize the available under-utilized frequency bands and enable the systems to dynamically access the spectrum, in this paper, we summarize existing recent advancements in spectrum sensing since inception to its current state, we also highlight the capabilities and drawbacks of narrowband and wideband SS techniques along with challenges and future research directions involved in their implementation.

Key words: *Cognitive radio, disaster response networks, Spectrum Sensing.*

1 Introduction

The portions of the electromagnetic spectrum frequencies from 30 Hz to 300 GHz are referred to as the radio spectrum, the allocation of radio spectrum is allocated by the International

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telecommunication Union ITU for a variety of radio-based technologies and applications, these technologies function on sold or licensed parts of the radio spectrum to operators of private radio transmission services such as mobile service providers, cellular networks, TV broadcasting stations and many others, since this recourse is a fixed resource while the number of users demanding access to this resource is exponentially increasing as time passes [1], the radio spectrum is now increasingly congested and the need for efficient and smart spectrum utilization is a driving and modern telecommunication trends and innovations such as CR, trunked radio, spread spectrum, frequency reuse and dynamic spectrum management [2].

The radio spectrum is divided into frequency bands, a frequency band is a small portion of the radio spectrum frequencies divided into frequency channels usually used for the same purpose [3], to prevent the interference among these bands and efficiently utilize these bands, similar services are allocated for the same contiguous group of bands, this is specified in the ITU bandplan which specifies how bands are used and shared to avoid interference and guarantee the compatibility of communicating devices.

The rapid growth in the demands of wireless devices specially with the static radio spectrum access management created a scarcity of available radio spectrum [4]. In year 2020, more than 50 billion of user devices will expectedly be connected around the globe, these devices are all wireless and are going to require an Internet access [5]. The static radio spectrum management will not be any more reliable and efficient to provide balanced access of this huge load on the internet. The reason is that static management of radio spectrum heavily allocates different portions of spectrum to a variety of technologies and users while leaving another portion of the spectrum used [6]. The inability to share the radio spectrum between different users will result in harmful denial of service events. Therefore, the radio spectrum scarcity is an annoying issue for the future of networking and telecommunication research community that needs to be focused on and addressed [7].

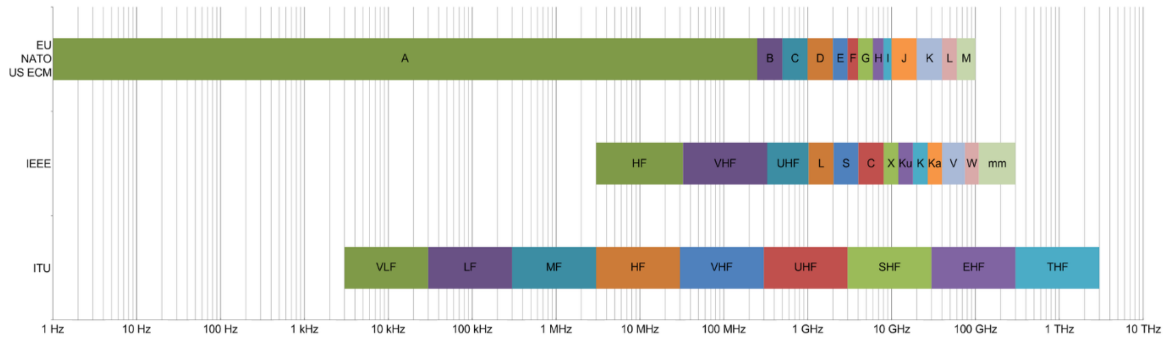

Figure 1: Radio bands designation standards.

One solution that has the potential to address this issue and many other issues regarding the radio spectrum scarcity problem is the use of CR technology [8], which was the issue of concern for researchers for almost last twenty years [9]. CR technology is an intelligent technology that enables CR enabled wireless nodes within the network to explore “sense” the radio spectrum surrounding environment, these devices can then decide what frequency channels are possible to be utilized, and finally reconfigure their transmission parameters to match the availability of communication channels making sure that energy consumption is minimal [10]. The CR technology is all about allowing cognitive users CUs to utilize the unused frequency bands of the licensed Primary Users PUs while they are idle and their dedicated frequency channels are vacant and evacuating these channels back when the licensed PUs are back so as to guarantee minimum levels of interference with PUs, these portions are referred to as spectrum holes [11].

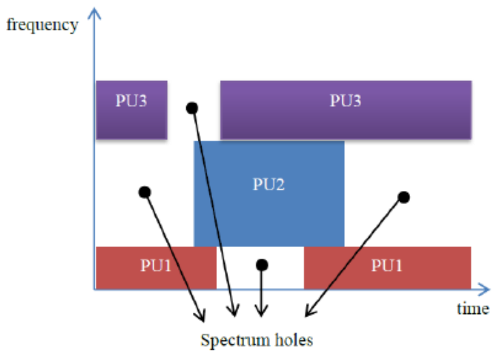

Figure 2: The spectrum hole concept.

Due to the necessity of efficient radio spectrum utilization and management, a number of radio SSSS techniques and methods were introduced in the last few years, based on their concern and functionalities, these methods are classified into two directions: narrowband spectrum access techniques and wideband spectrum access techniques [12]. Narrowband sensing techniques are concerned about the analysis of only a single channel at a particular time, the counterpart approach is wideband sensing techniques are concerned with the analysis of a number of frequency channels at a time where the spectrum is split into a number of frequency channels and then sensed in a sequential or simultaneous fashion, it is worthy to be mentioned here that sequential-sensing mechanisms are unreliable, costly and impractical timely communications since they consume more time and energy required for high rate (ADC), on the other hand, simultaneous sensing approaches are also impractical since they are based on a large number of sensing devices and joint synchronized function, this increases the complexity of the communication system and cant be afforded by simple user communicating devices [13], this has imposed the need to minimize the high number of signal samples acquired with compressive sensing [14]–[18], excessive research on SS has shown that the majority of the frequency channels over the wideband spectrum are not efficiently utilized [19]–[21], this has motivated researchers to focus on compressive sensing techniques and sub-Nyquist to enhance and fasten the process of spectrum sensing, which in turn will enhance the performance of the communication system where they are applied in [22].

2 Related Work

A considerable number of studies have reviewed the wideband SS mechanisms including compressive sensing, the authors in [4] have provided a review on latest advancements of SS developments and approaches, they also highlighted the achievements and drawbacks encountered with narrowband and wideband SS mechanisms and the challenges of their implementations, the authors in [23] introduced a comprehensive summary of the CR technology outlining the phases encountered in the cognitive cycle along with various aspects of different SS schemes, they also outlined the applications of the targeted schemes, the authors in [7] summarized the basics of radio SS in the CR technology functionality and its relevant issues and perspectives, they have also analyzed the SS from both cooperative and non-cooperative approaches along with system models for few detection, also the authors in [18] introduced the theory of compressive sensing and studies its features and functionalities when employed for CR systems. In [24], the authors categorized the wideband sensing techniques into two categories, (i) Nyquist wideband sensing, and, (ii) sub-Nyquist wideband sensing along with a comparison of their fundamental features and limitations, the authors in [25] reviewed the SS for CR spectrum access on an opportunistic basis and its related research directions along with a number of its relevant aspects for SS in CR. In [26], the authors introduced a survey of CR sensing algorithms, they also introduced the characteristics of related CR system as well as the techniques that enhance sensing parameters. The authors also considered the use of sub-Nyquist mechanisms such as compressive sensing techniques, finally, the authors in [27] have reviewed a few wideband SS techniques and provided a classification of these techniques.

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Table 1: Previous studies of Spectrum Sensing.

Ref.	Study issue	Covered	Ignored
[4]	SS in CR Networks	• Narrow band SS algorithms. • Wideband SS algorithms	• Interference minimization. • Sparsity level estimation.
[23]	SS for CR networks	• CR networks. • Spectrum management. • SS modeling.	• SS algorithms.
[7]	SS in CR Networks	• SS techniques. • Elements of SS modeling. • Interference problem.	• CR. • Sparsity level estimation.
[18]	Application of Compressive Sensing in CR Communications	• Compressive sensing. • Application analysis.	• Wideband SS mechanisms.
[24]	Wideband spectrum sensing	• Narrowband sensing mechanisms. • Wideband sensing mechanisms. • Sub-Nyquist sensing methods.	• Compressive wideband sensing. • Blind sensing. • Review of wideband sensing mechanisms.
[25]	SS algorithms for CR	• CR technology. • SS concept. • Spectrum detection mechanisms.	• Wideband SS mechanisms. • Compressive wideband sensing. • Blind sensing. • Review of wideband sensing mechanisms.
[26]	SS Algorithms for CR Networks	• Categories of spectrum sensing. • SS algorithms and parameters. • SS techniques. • Narrowband and wideband sensing concept. • Compressive sensing.	• Blind sensing. • Wideband SS mechanisms. • Interference minimization. • Sparsity level estimation.
[27]	Review of the spectrum sensing method	• Wideband sensing techniques. • Cooperative sensing.	• Compressive sensing. • Adaptive sensing. • Sparse basis detection.

Spectrum sensing is the term associated with wireless devices' ability to sense the surrounding environment for available spectrum communication channels. For CR networks, SS enables a device equipped with cognitive capability to explore its operating environment in terms of measuring, awareness and learning about spectrum availability and level, status and measurements of interference [8]. Once a vacant frequency band is found to be not efficiently utilized by the licensed PU at a certain instance, the cognitive users (CUs) can opportunistically utilize the spectrum, hence, devices can performe SS across the domains of time, frequency, and space, beamforming technology has advanced enough enabling a number of users to utilize the same frequency simultaneously in the same area [28]. therefore, if a PU is going in idle mode, secondary users may be granted spectrum opportunities for using communication channels that are not in service. Another issue in SS is related to the angle of arrivals of licensed users [7]. The PUs can also use their licensed frequency bands through spread-spectrum or frequency hopping, while CUs can simultaneously occupy the frequency bands provided that no interference to the PUs occurs, this can be attained if CUs occupy the frequency bands of the PUs according to an orthogonal code related to the codes being followed by the PUs [22]. This guarantee spectrum vacancies in code domain but secondary users' need to be aware of the codes adopted by the PUs and communication parameters. This is due to the fact that the detection of licensed users that are active is not an easy task, many research works on SS and specifically on PU activity detection according to node's measurements of cognitive users' SS and channel probing to collect immediate channel information needed for the users' devices which is also a critical components of CR networks. Generally, the SS cycle involves the performance of: (i) spectrum holes detection, (ii) identification of spectral availability, (iii) spatial directions calculation of the of detected signal of interference, and (iv) classification of signal acquired, the detection of available spectrum holes is considered to be the most critical task and can be performed using binary hypothesis-testing problem. Therefore, SS can be referred to as the exploration of vacant spectrum bands on a narrow frequency band which detects the availability or in availability of PUs activity in the underlying band [29].

3 Classification of Spectrum Sensing Algorithms

Spectrum sensing algorithms can be categorized to: (i) non-cooperative detection, (ii) and cooperative detection as shown in (Fig.3). cooperative detection algorithms are generally based on the detection of transmitted radios from a PU by the local observations of CUs. While non-cooperative detection approaches depend basically on assuming that the location of the PU is ambiguous to the CU's communicating device. Based on that, secondary users need to rely only on the detection of weak PU's signals and perform SS only using their own local observations. This is because CU's devices are not normally aware of status of spectrum domain around. As a consequence, harmful interference with PU s is not possibly completely avoided. In addition to that, PU activity detection doesn't completely prevent a hidden terminal problem. There are three major schemes that are usually utilized for PU activity detection which are: (i) matched filter detection, (ii) energy detection, and, (iii) features detection and are discussed in this section.

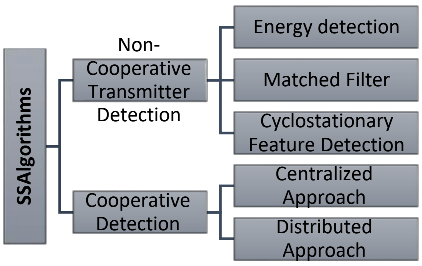

Figure 3: Spectrum Sensing Approaches.

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3.1 Non-cooperative/Transmitter Detection Approaches

Coherent signal detection techniques are those techniques in which communicating devices need to have a prior information about the status of the signal of the PU for the sake of comparison of a specific radio feature to the signal of the CU. While in non-coherent detection methods a pre-defined threshold to compare the received signal based on the characteristics that are not depending on information about the signal of the PU [24]. An alternative classification of SS techniques can be made based on bandwidth where they can be classified into wideband and narrowband detection techniques [30]. The reason behind naming Non-cooperative/transmitter detection with this name is because CR's sensing is only capable of detecting a signal that is originating from transmitter of the PU. This approach of detection can be classified to the following:

3.1.1 Energy Detection

Energy detection is a common technique applied for SS to determine the activity or inactivity of a PU regardless of information about the status of the PU activity. It is resistant to the change in the PU activity since it does not require any awareness of the PU signal. In this technique, the received signal is used to measure the energy level of the PU signal, and the signal in the channel is detected if the signal energy of this channel was found to be above than signal noise [31]. Basically, the component of energy detection is used to filter out the noise from undesired channels [32]. The samples that are produced by the filter are then squared and accumulated to form the energy of the signal. In the last step, the resulting value is estimated with a certain threshold measurement to find out if a PU is active or idle as shown in Fig 4. The challenging task in this technique is setting the accurate threshold which should be able to recognize the signal from noise. In conclusion, this approach of detecting signal energy is the easiest approach practically used for detecting the energy of the signal provided that a previous information about the level of noise is required, otherwise, the absence of this knowledge degrades the performance of the energy detector [33].

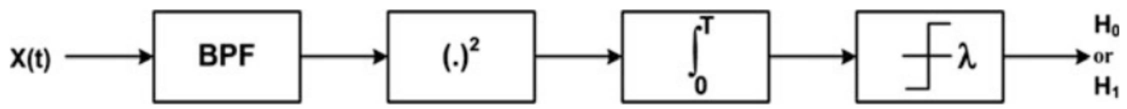

Figure 4: Enery detection based SStechnique.

3.1.2 Matched Filter Detection

The working principle of matched filter sensing techniques is based on performing a comparison between the received signal and the pilot samples obtained as a result of the same transmitting device [34]–[36]. The test statistic is calculated using the pilot samples and then

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it is compared to a predefined threshold. If the statistic is found to be higher than the value of the threshold, the signal of the PU is considered to be present. This procedure is shown in Fig.5.

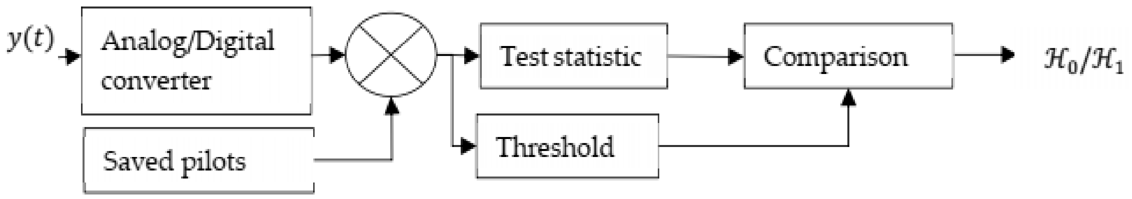

Figure 5: Matchd filter based SStechnique.

The threshold value is proportional to the noise signal detected in the signal which is received. Regarding the energy detection technique, the implementation of a threshold whose value is statically set can produce less exact readings due to its uncertainty of noise which is a critical challenging task. For this reason, the authors of [36] investigated the use of a threshold whose value is dynamically set for the sake of dynamic selection of the value to obtain a better performance of detection procedure adopted. In conclusion, matched filter techniques are reliable and their performance is optimized because few samples are needed to obtain a desired level of signal detection, while they are found to be extremely applicable since they usually require previous knowledge about the PU signal while this knowledge can't be always obtained.

Cyclostationary Feature Detection

In this technique, the identification of PU activity signals is performed based on deterministic or statistical properties of PU activity signals. Generally, feature detection is performed according to signal features that were extracted and hence; it can differentiate between signals with different features [37]. Feature detection requires more processing capabilities than other previous detection techniques.

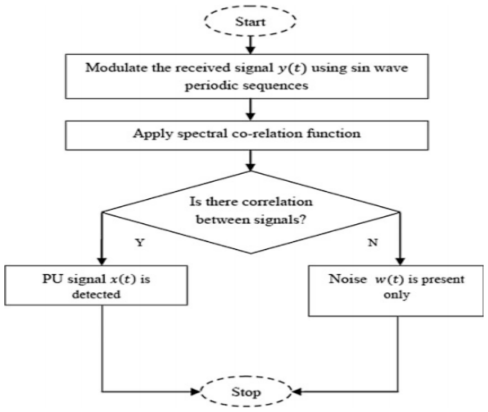

Figure 6: Flow sequence of the cyclostationary technique.

Cyclostationarity-based detectors are such an important subclass of feature detectors, these detectors are more reliable than energy-based detection from perspective of uncertainty of noise signal, this is due to the fact that noise signals are not considered as a cyclostationary feature [36]. In spite of that, Cyclostationary feature detection may highly be affected by synchronization errors producing carrier frequency and sampling clock frequency offsets. This feature detection technique which is interestingly applied in CR networks for SS technique because distinguishes the primary signal from interference and the noise signals [38].

Table 2: Advantages and disadvantages of non-cooperative sensing techniques.

Sensing Technique	Class	Advantages	Limitations
Energy Detector	Sensing	• Non-coherent. • Designed simply. • Less complex.	• Can't distinguish primary signal from noise. • Unable to work well with low SNR. • Suffers with noise uncertainty
Matched Filter	Sensing	• Better sensing results. • Maximum SNR received. • High processing gain.	• Requires primary network awareness. • primary network specifies computational complexity. • Synchronization requires a dedicated sensing receiver.
Feature Detection	Sensing	• Less sensing time for energy detection. • Reliable sensing performance. • Good for signals with low SNR. • Reliable with noise uncertainty	• Require primary network awareness. • Greater sensing time for to energy detection.

3.2 Cooperative Detection

The problem of hidden terminal is such a critical challenge in SS. It results from CR shadowing and also due to the negligible SNR value of the received signal, this signal is unable to detect the activity of the PU in a reliable manner. The functionality of CR technology is based on the assumption that the channel which was sensed is vacant and starts to transmit over that channel while the PU is still active which results in interference with the PU. Several challenges arise in SS which can degrades sensing reliability. Furthermore, every local SS technique has its own pros and cons, still, no scheme is found to be an optimal scheme for all application scenarios. Due to this, it is important for a number of CUs who are randomly distributed to cooperate in order to find a potential solution to resolve the problems arising from SS techniques that are locally performed. Cooperative detection simply means that multiple CR-enabled devices are capable of cooperatively and coordinately performing the task of spectrum sensing. Many studies concluded that cooperative SS has a large potential to maximize the opportunities of fading channels detection [39]. In CR systems, cooperative sensing is similar to local decision making which is performed by wireless sensor nodes in WSNs, where decisions are locally made by each node , these decisions are then forwarded to fusion center (FC) to finally decide based on a certain predefined fusion rule [39]. The wireless transmission medium is such a distinguishing feature between CR and WSNs. Different from WSNs, CR and fusion centers FCs are geographically distributed over distant locations. This results in a serious challenge for cooperative SS, because channel sensing -performed from PUs to CUs- followed by reporting channels – performed from CUs to FCs- usually suffer from fading or are heavily shadowed [7]. Therefore, the purpose of cooperative SS is to exploit the changes occurring to CU's locations to finally come up with a unified and general decision that is to be utilized by all CUs [40]. Depending on the approaches used by CUs to broadcast their information sensed from surrounding environment, in this sensing approach two mechanisms of detection exist as illustrated below.

3.2.1 Centralized Cooperative Spectrum sensing (CCSS)

In this sensing approach, all CUs perform the sensing of the band of interest each using the same or different sensing techniques, and finally, these nodes share their decisions which were locally made via common control channel CCC to a central unit [41]. Then, the data received is fused to make a final decision based on the status of the PU, centralized cooperative SS can be classified into both CCSS and DCSS according to the way fusion process is performed, i.e. the cooperative system is considered to be a centralized model if the fusion process is done at a central base station, while in CR ad hoc networks (CRAHNs) that employee no base station and hence; one of the cooperating cognitive nodes coordinates both the synchronization and fusion processes [42].

3.2.2 Distributed Cooperative Spectrum Sensing (DCSS)

Here, cognitive nodes exchange the information sensed rather than depending on a centralized FC and ultimately make one global decision after repetitive trading of the sensed information. In this way, distributed cooperative SS systems might be cost efficient up to a higher extent than that of non-distributed models since their deployment and initiation don't imply any dedicated infrastructure [43]. There are many cooperative SS algorithms that have been employed to coordinate the sensing information at different cognitive nodes, one of these algorithms is the discrete time gossip protocol where a CU senses a desired band during a particular slot of time and consequently sends its sensed data to a group of neighboring CUs selected at random [44]. Several dissemination strategies for sensing information between CUs have also been proposed , in the majority of these strategies; a single group of cooperating CUs share the decisions they have locally made during a particular slot of time and then a CU belonging to this group transmits the data received to a randomly adjacent node in his neighboring nodes subsequently and repetitively until sensing information is delivered to all CUs [45].

4 Conclusion

The functionalities of CR are able to cope with growing requirements of spectrum in next generation communication systems and networks, many wireless technologies and devices are competing to gain access to the Internet on a rapidly growing scale, this means that next generation communication systems and networks will confront a challenging task of spectrum opportunistic access that has to be addressed, in this paper we provided a review of the recent advances and challenges of CR associated with SS research, a classification of SS techniques was provided where these techniques were categorized into cooperative and non-cooperative perspectives, each of which had its pros and cons, design and selection of a reliable algorithm for feature and spectrum detection depends highly on the area of application and the PU system, detection algorithms should be primarily system oriented, i.e. there is no detection algorithm characterized as suitable for all applications, Therefore, feature detection or matched filter techniques are useful whenever a specific performance is desired, while energy detection is an alternative feasible algorithm that aids when computational perspectives are considered.

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References

[1] K. Leyton-Brown, P. Milgrom, and I. Segal, "Economics and computer science of a radio spectrum reallocation," *Proc. Natl. Acad. Sci. U. S. A.*, vol. 114, no. 28, pp. 7202–7209, 2017, doi: 10.1073/pnas.1701997114.

[2] N. Islam, G. S. Sheikh, and Z. Islam, "ACognitive Radio Ad Hoc Network ' s Based Disaster Management Scheme with Efficient Spectrum Management , Collaboration and Interoperability," vol. 11, no. 1, 2017.

[3] P. K. Pagadala, "Efficient utilization of spectrum bandwidth using Cognitive Radio to improve throughput in wireless adhoc networks Efficient utilization of spectrum bandwidth using Cognitive Radio to improve throughput in wireless adhoc networks," no. January 2013, 2017.

[4] Y. Arjoune and N. Kaabouch, "A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions," *Sensors (Switzerland)*, vol. 19, no. 1, 2019, doi: 10.3390/s19010126.

[5] A. Al-Fuqaha, M. Guizani, and M. Mohammadi, "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications," *Jisuanji Xuebao/Chinese J. Comput.*, vol. 41, no. 7, pp. 1448–1475, 2018, doi: 10.11897/SP.J.1016.2018.01448.

[6] J. H. Park, W. C. Lee, J. P. Choi, J. W. Choi, and S. Bin Um, "Applying Case-Based Reasoning to Tactical Cognitive Sensor Networks for Dynamic Frequency Allocation," pp. 1–22, 2018, doi: 10.3390/s18124294.

[7] S. Pandit and G. Singh, *Spectrum Sensing in Cognitive Radio Networks: Potential Challenges and Future Perspective*. 2017.

[8] K. F. Alaqad and M. A. Burhanuddin, “Cognitive Radio-based Routing Protocols for Disaster Area Networks ; Research challenges and directions,” *Int. J. Adv. Sci. Technol.*, vol. 28, no. 1, pp. 521–538, 2019.

[9] F. Al-Turjman, “Cognitive routing protocol for disaster-inspired Internet of Things,” *Futur. Gener. Comput. Syst.*, vol. 92, pp. 1103–1115, 2019, doi: 10.1016/j.future.2017.03.014.

[10] P. K. D. Pramanik, S. Pal, and P. Choudhury, *Beyond Automation: The Cognitive IoT. Artificial Intelligence Brings Sense to the Internet of Things*, no. August. 2018.

[11] S. S. Oyewobi and G. P. Hancke, “A survey of cognitive radio hando ff schemes , challenges and issues for industrial wireless sensor networks (CR-IWSN),” *J. Netw. Comput. Appl.*, vol. 97, no. September, pp. 140–156, 2017, doi: 10.1016/j.jnca.2017.08.016.

[12] A. Ali and W. Hamouda, “Advances on Spectrum Sensing for Cognitive Radio Networks: Theory and Applications,” *IEEE Commun. Surv. Tutorials*, vol. 19, no. 2, pp. 1277–1304, 2017, doi: 10.1109/COMST.2016.2631080.

[13] Q. Lu, S. Yang, and F. Liu, “Wideband spectrum sensing based on Riemannian distance for cognitive radio networks,” *Sensors (Switzerland)*, vol. 17, no. 4, 2017, doi: 10.3390/s17040661.

[14] Y. Arjoune, N. Kaabouch, H. El Ghazi, and A. Tamtaoui, “Compressive sensing: Performance comparison of sparse recovery algorithms,” *2017 IEEE 7th Annu. Comput. Commun. Work. Conf. CCWC 2017*, 2017, doi: 10.1109/CCWC.2017.7868430.

[15] F. Salahdine, N. Kaabouch, and H. El Ghazi, “Bayesian compressive sensing with circulant matrix for spectrum sensing in cognitive radio networks,” *2016 IEEE 7th Annu. Ubiquitous Comput. Electron. Mob. Commun. Conf. UEMCON 2016*, pp. 1–6, 2016, doi: 10.1109/UEMCON.2016.7777851.

[16] F. Salahdine and H. El Ghazi, “A real time spectrum scanning technique based on compressive sensing for cognitive radio networks,” *2017 IEEE 8th Annu. Ubiquitous Comput. Electron. Mob. Commun. Conf. UEMCON 2017*, vol. 2018-Janua, pp. 506–511, 2017, doi: 10.1109/UEMCON.2017.8249008.

[17] F. Salahdine, N. Kaabouch, and H. El Ghazi, “A survey on compressive sensing techniques for cognitive radio networks,” *Phys. Commun.*, vol. 20, pp. 61–73, 2016, doi: 10.1016/j.phycom.2016.05.002.

[18] S. K. Sharma, E. Lagunas, S. Chatzinotas, and B. Ottersten, “Application of compressive sensing in cognitive radio communications: A survey,” *IEEE Commun. Surv. Tutorials*, vol. 18, no. 3, pp. 1838–1860, 2016, doi: 10.1109/COMST.2016.2524443.

[19] A.-A. Boulogeorgos and G. Karagiannidis, “Low-cost Cognitive Radios against Spectrum Scarcity,” pp. 2–5.

[20] M. López-Benítez, A. Umbert, and F. Casadevall, “Evaluation of spectrum occupancy in Spain for cognitive radio applications,” *IEEE Veh. Technol. Conf.*, pp. 1–5, 2009, doi: 10.1109/VETECS.2009.5073544.

[21] M. A. McHenry, P. A. Tenhula, D. McCloskey, D. A. Roberson, and C. S. Hood, "Chicago spectrum occupancy measurements & analysis and a long-term studies proposal," *ACM Int. Conf. Proceeding Ser.*, vol. 222, 2006, doi: 10.1145/1234388.1234389.

[22] A. Jamoos, O. Najajri, and A. Abdou, "Cognitive radio-based solutions for spectrum scarcity in Palestine," *Int. J. Mob. Netw. Des. Innov.*, vol. 9, no. 1, pp. 14–23, 2019, doi: 10.1504/IJMNDI.2019.098234.

[23] M. S. Gupta and K. Kumar, "Progression on spectrum sensing for cognitive radio networks: A survey, classification, challenges and future research issues," *J. Netw. Comput. Appl.*, vol. 143, no. January, pp. 47–76, 2019, doi: 10.1016/j.jnca.2019.06.005.

[24] J. M. N. Vieira, A. M. Tomé, and D. Malafaia, "Wideband spectrum sensing for Cognitive Radio," *Eur. Signal Process. Conf.*, vol. 2016, no. July, pp. 596–600, 2014.

[25] I. Kakalou, D. Papadopoulou, T. Xifilidis, K. E. Psannis, K. Siakavara, and Y. Ishibashi, "A survey on spectrum sensing algorithms for cognitive radio networks," *2018 7th Int. Conf. Mod. Circuits Syst. Technol. MOCAST 2018*, pp. 1–4, 2018, doi: 10.1109/MOCAST.2018.8376562.

[26] I. Kakalou, D. Papadopoulou, T. Xifilidis, K. E. Psannis, K. Siakavara, and Y. Ishibashi, "A survey on spectrum sensing algorithms for cognitive radio networks," *2018 7th Int. Conf. Mod. Circuits Syst. Technol. MOCAST 2018*, vol. 1, no. 3, pp. 1–4, 2018, doi: 10.1109/MOCAST.2018.8376562.

[27] L. De Vito, "A review of wideband spectrum sensing methods for Cognitive Radios," *2012 IEEE I2MTC - Int. Instrum. Meas. Technol. Conf. Proc.*, pp. 2257–2262, 2012, doi: 10.1109/I2MTC.2012.6229530.

[28] L. M. Marrero, D. Alejandro, U. Villalonga, and E. H. Inguanzo, "Cognitive radio platforms: a survey.," *Rev. Telemática*, vol. 15, no. 1, pp. 69–79, 2016.

[29] Y. Saleem and M. H. Rehmani, "Primary radio user activity models for cognitive radio networks: A survey," *J. Netw. Comput. Appl.*, vol. 43, pp. 1–16, 2014, doi: 10.1016/j.jnca.2014.04.001.

[30] M. Hajiabadi, H. Khoshbin, and G. A. Hodtani, "Cooperative spectrum estimation over largescale cognitive radio networks," *IET Signal Process.*, vol. 11, no. 8, pp. 1006–1014, 2017, doi: 10.1049/iet-spr.2016.0727.

[31] P. R. Nair, A. P. Vinod, and A. K. Krishna, "A fast two stage detector for spectrum sensing in cognitive radios," *IEEE Veh. Technol. Conf.*, 2011, doi: 10.1109/VETECF.2011.6092897.

[32] P. R. Nair, A. P. Vinod, and A. K. Krishna, "An adaptive threshold based energy detector for spectrum sensing in cognitive radios at low SNR," *12th IEEE Int. Conf. Commun. Syst. 2010, ICCS 2010*, pp. 574–578, 2010, doi: 10.1109/ICCS.2010.5686712.

[33] Y. Liu *et al.*, "Adaptive double threshold energy detection based on Markov model for cognitive radio," *PLoS One*, vol. 12, no. 5, pp. 1–18, 2017, doi: 10.1371/journal.pone.0177625.

[34] F. Salahdine, H. El Ghazi, N. Kaabouch, and W. F. Fihri, "Matched filter detection with dynamic threshold for cognitive radio networks," *Int. Conf. Wirel. Networks Mob. Commun. WINCOM 2015*, 2016, doi: 10.1109/WINCOM.2015.7381345.

[35] C. Jiang, Y. Li, W. Bai, Y. Yang, and J. Hu, "Statistical matched filter based robust spectrum sensing in noise uncertainty environment," *Int. Conf. Commun. Technol. Proceedings, ICCT*, no. 2012, pp. 1209–1213, 2012, doi: 10.1109/ICCT.2012.6511381.
[36] X. Zhang, R. Chai, and F. Gao, "Matched filter based spectrum sensing and power level detection for cognitive radio network," *2014 IEEE Glob. Conf. Signal Inf. Process. Glob. 2014*, pp. 1267–1270, 2014, doi: 10.1109/GlobalSIP.2014.7032326.
[37] O. Elnahas and M. Elsabrouty, "Cyclostationary-Based Cooperative Compressed Wideband Spectrum Sensing in Cognitive Radio Networks," *2017 Wirel. Days, WD 2017*, pp. 77–82, 2017, doi: 10.1109/WD.2017.7918119.
[38] P. Semba Yawada and A. J. Wei, "Cyclostationary Detection Based on Non-cooperative spectrum sensing in cognitive radio network," *6th Annu. IEEE Int. Conf. Cyber Technol. Autom. Control Intell. Syst. IEEE-CYBER 2016*, pp. 184–187, 2016, doi: 10.1109/CYBER.2016.7574819.
[39] M. Hejazi and B. Abolhassani, "Cyclostationarity-Based Multi-Antenna Cooperative Spectrum Sensing in Cognitive Radio Networks over Correlated Fading Channels," *26th Iran. Conf. Electr. Eng. ICEE 2018*, pp. 627–632, 2018, doi: 10.1109/ICEE.2018.8472493.
[40] X. Liu, F. Li, and Z. Na, "Optimal Resource Allocation in Simultaneous Cooperative Spectrum Sensing and Energy Harvesting for Multichannel Cognitive Radio," *IEEE Access*, vol. 5, no. 8, pp. 3801–3812, 2017, doi: 10.1109/ACCESS.2017.2677976.
[41] S. C. Shinde and A. N. Jadhav, "Centralized cooperative spectrum sensing with energy detecion in cognitive radio and optimization," *2016 IEEE Int. Conf. Recent Trends Electron. Inf. Commun. Technol. RTEICT 2016 - Proc.*, pp. 1002–1006, 2017, doi: 10.1109/RTEICT.2016.7807980.
[42] A. Haldorai and U. Kandaswamy, "Cooperative spectrum handovers in cognitive radio networks," *EAI/Springer Innov. Commun. Comput.*, pp. 1–18, 2019, doi: 10.1007/978-3-030-15416-5_1.
[43] G. Sharma and R. Sharma, "Distributed cooperative spectrum sensing over different fading channels in cognitive radio," *2017 Int. Conf. Comput. Commun. Electron. COMPTELIX 2017*, pp. 107–111, 2017, doi: 10.1109/COMPTELIX.2017.8003947.
[44] B. Aygun and A. M. Wyglinski, "A voting-based distributed cooperative spectrum sensing strategy for connected vehicles," *IEEE Trans. Veh. Technol.*, vol. 66, no. 6, pp. 5109–5121, 2017, doi: 10.1109/TVT.2016.2626274.
[45] A. Vosoughi, J. R. Cavallaro, and A. Marshall, "Trust-Aware Consensus-Inspired Distributed Cooperative Spectrum Sensing for Cognitive Radio Ad Hoc Networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 2, no. 1, pp. 24–37, 2016, doi: 10.1109/tccn.2016.2584080.