International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 04 | Apr 2022 www.irjet.net p-ISSN: 2395-0072

Signal Classification and Identification for Cognitive Radio: A Review

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Abstract - *The need for increasing data rates in wireless communication has grown tremendously over the last few decades. The burgeoning demand for wireless devices has been stifled by the spectrum access regulation. Only a tiny amount of the whole spectrum is offered to open users, while a big portion is given to licenced users. However, because the unlicensed spectrum is used more than the licenced spectrum, the FCC was obliged to create a regulation to ensure that the limited bandwidth is used efficiently. The licenced spectrum has a far lower spectral occupancy than the unlicensed spectrum. Cognitive radio has evolved as a remedy to this wasteful use of licenced spectrum; it identifies and makes available to unlicensed users the unused fraction of the licenced spectrum known as white space. It is necessary to recognise and categorise the signals before sending the white space to the secondary use for signal transmission so that the cognitive radio can function efficiently.*

***Key Words*:** Signal Classification, Identification of Signals, Cognitive Radio, Frequency of Cognitive, Time detection

1. INTRODUCTION

The term "cognitive radio" comes from the word "cognitive," which refers to the process of gaining information by logic, intuition, or perception. It's a brand-new technology that looks for white spaces in the radio spectrum. It allows the unlicensed user to utilise the licenced bands without interfering with the licenced user in any way. The principal user is also known as the licenced user (PU). Secondary users are those who do not have permission to listen to the licenced musicians

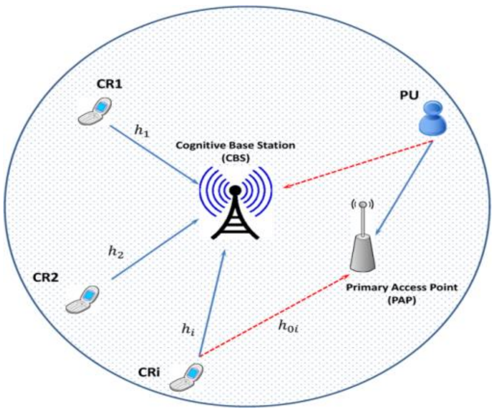

Figure-01: System Model for Cognitive Radio

1.1 Characteristics of Cognitive Radio (CR)

CR is an intelligent radio system that checks the availability of the spectrum and utilized them efficiently. CR has the following characteristics which help in achieving this goal:

1) Flexibility: Cognitive radio should have the ability to adjust parameters such as data rate and modulation style.

2) Agility: CR should be able to function in a variety of spectrum bands to take advantage of white spaces seen in various frequency bands.

3) Sensing: CR should be able to detect spectrum gaps and offer an overview of radio spectrum usage by sensing the RF environment and internal functioning parameters.

4) Networking: To achieve synergy in the use of radio resources, CR should be able to communicate between different nodes of wireless communication. Information sharing and decision-making on radio resources are done cooperatively.

1.2. Different Types of Signals

Cognitive radio technology was utilised to take advantage of the radio spectrum for a variety of transmissions. IEEE 802.22 WRAN, NTSC, PAL, and SECAM are examples. The IEEE 802.22 protocol made use of previously unutilised bandwidth in the television frequency range. This signal is intended to work in the television broadcast band. The National Television System Committee (NTSC) is a traditional analogue television system that is mostly utilised in Western nations. The colour encoding scheme Phase Alternating Line (PAL) is used in analogue television. In an analogue colour television system, Sequential Color with Memory (SECAM) is employed.

2. LITERATURE SURVEY

In the literature review studied some research papers related to cognitive radio, the summary of all research papers is given:

[1] Gandetto et al (2006) These authors researched his work "Distributed Cooperative Mode Identification For Cognitive Radio Applications" and the conclusion is given that, In the context of Cognitive Terminals, the mode Identification Frequency Hopping Code Division Multiple

Access (FHCDMA) and Direct Sequence Code Division Multiple Access (DS-CDMA) are the two types of air interfaces classified. A binary and distributed likelihood test was used to create a closed-form for error probability; also, the error rate was calculated and compared to theoretic formulae, which showed similar behaviour and satisfactory results. Ongoing research focuses on the resolution of many hypotheses using distributed decision tests that take into consideration new air interfaces such as multi-carrier methods and novel methodology for combined position and model estimation.

[2] Ganesan et al (2007) These authors research his work "Cooperative Spectrum Sensing in Cognitive Radio" and the conclusion are given that, We've demonstrated how collaboration improves the agility of cognitive radio networks. We first looked at a basic two-user cooperative cognitive network and demonstrated increased agility by making use of the inherent asymmetry. We looked at two schemes with varying degrees of cooperation: (1) non-cooperative (NC), in which each user detects the primary user independently, but the first user to do so informs the other cognitive users via a central controller, and (2) cooperative (TC), in which users follow the AF cooperation protocol to reduce detection time. We've proven that collaboration between cognitive nodes improves the network's overall agility. We also looked at how power constraints affect cooperation schemes and other key features of such networks. We've also expanded our collaboration strategy to multicarrier networks with a maximum of two users per carrier and derived agility gain expressions.

[3] Awais Khawar (2010) The author studied his research work regarding "Spectrum Sensing Security in Cognitive Radio Networks" and the conclusion is given that, The use of signal classifiers and clustering algorithms for DSA has opened up new research avenues. They looked into three different sorts of signal classifier assaults. The signal classifier was the self-organizing map (SOM), and the decision boundary methods were K-means and a weighted hierarchical clustering algorithm. For starters, it was demonstrated analytically that such an assault is viable in a simpler (one-dimensional) instance. Then, with Matlab, more complicated instances were simulated. Connection, point cluster, and random noise assaults on signal classifiers were shown to be successful in simulations. This revealed that an enemy user may easily manage a machine learning environment because if it can learn from the environment, it can also be taught by the environment.

[4] Rehan Ahmed (2010) The author studied his research work regarding the "Detection ff Vacant Frequency Bands In Cognitive Radio" and his conclusion are given that, Spectrum is a very valuable resource in wireless communication systems, and it has been a hot topic of debate, study, and development efforts for decades. CR has evolved into an exciting and brilliant notion, as one of the hard works to utilise the available spectrum more ingeniously through opportunistic spectrum utilisation. One of the most important aspects of sensing in CR is the accessible spectrum options. By considering different proportions of the spectrum space, topics connected to spectrum sensing and its prospects are re-evaluated. Various features of the spectrum sensing assignment are thoroughly addressed. Several sensing strategies are discussed, and collaborative sensing is well-regarded as a solution to several common spectrum sensing challenges. We briefly presented the cooperative spectrum sensing approach and its benefits in boosting the agility of CR networks in our simulations. To begin, we looked at two user cooperative networks and studied the improvements in detection time with relay users, as well as the associated gains in agility gain. Then we expanded our collaboration scheme to include multi-user multi-carrier networks and recognised the unique conditions that enable agility benefits. We looked at both the cooperative and non-cooperative cases, using different levels of collaboration and non-cooperation. In the non-cooperative situation, each CR detects the existence of the PU independently and vacates the band without alerting the others, but in the cooperative case, the first CR to detect the presence of the PU notifies the others. We found from simulation findings that detection time is improved and that substantial agility gain may be achieved through collaboration.

[5] Zhengyi et al (2010) authors researched their work "Fast Detection method In Cooperative Cognitive Radio Networks" and the conclusion is given that, For cooperative cognitive radio networks, a quick detection approach, SPRT-TW for individual detection and weighted K out of N fusion rule for global detection, has been developed. It is demonstrated that the proposed SPRT-TW takes the shortest detection time when compared to the traditional NP detection method and the original SPRT and that the weighted fusion rule takes fewer individual decisions (and thus is faster) than the original fusion rule to reach the global decision. The characteristics of wireless channels are taken into account in our method.

[6] Sepideh Zarrin (2011) Author researched his work "Spectrum Sensing in Cognitive Radio Networks" and the conclusion is given that, The method provides for modelling and adapting uncertainties and correlations in the cooperative sensing system, as well as inferring likelihood functions through belief propagation. For hard, soft, and quantized local choices, we developed the NP-based LRT at the FC. Unlike most previous research, we take into account fading and noise in the transmission channels. As a result, we suggested a linear composite hypothesis testing technique that requires no previous information or estimations of the unknown parameters and performs quite similarly to the optimum LRT for known parameters. We also looked into the quickest change detection in cognitive radios for spectrum sensing. We calculated the ideal CUSUM test statistics in each case by presenting multiple cooperative fastest sensing methodologies in cognitive radios. We presented linear test-based CUSUM methods to address the problem of uncertain main signal and channel statistics in cognitive radios, which, unlike previous processes, do not involve parameter estimates or iterative algorithms.

[7] R. Castro et al (2012) These authors researched his work "Modulation Classification in Cognitive Radio" and the conclusion is given that, CSS and cyclo stationarity were compared and contrasted as front-end methods. The use of SVMs as the foundation classifiers for AMC systems is demonstrated, with experimental results. The categorisation of BPSK, 4PAM, 8PSK, and 16QAM modulations yielded the results presented in this chapter. For the set of modulations used, the CSS front end paired with the linear kernel SVM classifier produced good results and proved to be practical for implementation in an FPGA and real-time processing. In addition, a synthesizable CSS-SVM architecture was devised, which provided good AMC results while utilising the available FPGA resources efficiently.

[8] Curtis M. Watson (2013) The author studied his research in his works "Signal Detection and Digital Modulation Classification Based Spectrum Sensing for Cognitive Radio" and his conclusion are given that, the algorithmic creation of a radio identification spectrum sensing architecture may better distinguish the main users from secondary users by characterising every detected signal in the spectrum. We assumed that we knew where the primary user's licenced spectrum was located, as well as the modulation types that a primary user might utilise. We analysed and matched the unknown signal's discovered features to the known parameters of the main user. Because of this comparison, our spectrum sensing architecture delivers more meaningful information regarding spectrum availability to cognitive radio. The first contribution of our research is a narrowband signal detection algorithm that attempts to locate all narrowband signals in a received wideband signal with higher accuracy than the energy detection algorithm at estimating the signal's carrier frequency and bandwidth, especially at lower SNR values. The second edition of our study is a constellation-based digital modulation classification method that uses the constellation structure to increase classification accuracy over a series of literature comparisons, with the most striking improvement of 61.4 percentage points at 0 dB SNR. Finally, our study has produced a spectrum sensing architecture that generates an informative spectrum activity report that can be used by a cognitive radio to identify spectrum access possibilities more accurately and with a reduced main user false alarm rate.

[9] Idris A. Yusuf (2017) The author researched his work "Optimizing Cooperative Spectrum Sensing in Cognitive Radio Networks using Interference Alignment and Space-Time Coding" and conclusion are given that, ST-WF has a larger capacity per antenna than SWF, and although has a higher channel interruption probability than SWF, its transmission is comparable to block transmission, allowing it to function under settings more suitable for CR networks. Second, to improve the accuracy of TO detection, this study employs a twofold threshold energy detection (ED) approach, in which the FC gets two types of data on which to make its choice. With a wider range of values accessible to the FC, the FC's detection accuracy improves, resulting in a larger number of TOs.

[10] Ayush Tiwari (2018) The author researched his study about"Comparison of Statistical Signal Processing and Machine Learning Algorithms as Applied to Cognitive Radios" and his conclusion is given that, The performance of machine learning algorithms is much better than that of signal processing techniques. By increasing the number of training samples in supervised learning (k-nearest neighbour), accuracy may be greatly improved. While the number of samples has little influence on the efficacy of unsupervised learning methods (such as the EM algorithm), there must be enough samples such that the data is statistically meaningful.

[11] Mashta et al (2019) authors studied his research work about "A Classification of the Spectrum Sensing Techniques for Cognitive Radio" and the conclusion is given that, **in** the categorisation of spectrum sensing techniques; single-user sensing algorithms were split into coherent and non-coherent sensing algorithms. Each strategy was thoroughly detailed, including basic concepts, benefits, and drawbacks. In addition, we compared narrowband and wideband spectrum sensing procedures and tallied the difficulties in implementing them. We also covered the fundamentals of cooperative sensing and interference-based sensing. Finally, while presenting the latest cognitive radio standards, the current industry effort in terms of standard requirements is addressed.

[12] Tarhuni et al (2019) all authors researched their works on "Implementation of Machine Learning Spectrum Sensing For Cognitive Radio Applications" and the conclusion is given that, two spectrum sensing schemes are used in cognitive radio systems' performance An energy detector-based spectrum sensing scheme and a machine learning polynomial classifier spectrum sensing strategy are implemented utilising NI USRP software-defined radio devices in the experiments. The misclassification rate for the two systems is displayed under various SNR circumstances and sensing durations.

[13]Sarala et al (2019) All authors research their works about "Spectrum energy detection in cognitive radio networks based on a novel adaptive threshold energy detection method" and conclusions are given that, identify the savvy signals in a spectrum band that are artistically clever. Recognizing the underutilised spectrum in the execution of an energy innovation was evaluated in this suggested study activity. Both an AWGN on the Pd and Pfa of a sense node comprises expressions in the theoretical foundation of the investigation. Based on the threshold setting of the SU energy detection methodology, simulation results reveal that the proposed ATSED approach outperforms AWGN in terms of execution. The likelihood of SNR fluctuates depending on the likelihood of false alarms and numerous bandwidth variables. Identity probability is influenced by SNR. As the SNR rises, Pd rises with it, and the improvement in symptoms implies that the symbol 1.0 is more likely changes are also dependent on the time-bandwidth factor. As the chance of detecting multiple time-bandwidths decreases, the frequency of detection of multiple time-bandwidths decreases.

[14] Md Faisal Kabir (2020) The author researched his works about "Application of Deep Learning in Deep Space Wireless Signal Identification for Intelligent Channel Sensing" and his conclusion is given that, To detect signal modulation, two deep learning algorithms were used. A dataset acquired from the NASA SCaN testbed was used to train both the MLP and CNN models. It was a binary classification issue utilising BPSK and QPSK modulation methods. We constructed three separate datasets by extracting different characteristics from the source complicated dataset. The MLP model was trained using three of these datasets. Following that, the results were compared to the best-performing dataset. The CNN model was then trained using two of the best-performing datasets, which were then compared to the best-performing dataset. With an F1 score of 0.98, the FFT dataset fared best with the CNN model. We evaluated the findings and discovered that CNN outperforms MLP in terms of F1 scores. Future research might focus on establishing processes for incorporating signal recognition into the ICS cognitive cycle. More modulation schemes, such as 8-PSK, 16-QAM, 64-QAM, and so on, may be added to the dataset to make it a multiclass classification issue and see how well the model works. More machine learning algorithms, such as SVM, RNN, and others, may be used to compare existing findings and evaluate which one works best for these types of deep space signal samples. We may also compare the time requirements of various strategies.

[15] Solanki et al (2021) These authors studied his research work on "Deep Learning for Spectrum Sensing in Cognitive Radio" and the conclusion is given that, In cognitive radio, spectrum detection is a major problem. For many reasons, traditional spectrum sensing technologies have inherent drawbacks to spectrum sensing. This study proposes the "DLSenseNet" deep neural network-based spectrum sensing model. In comparison to other sensing models, such as the convolutional neural network, LSTM, CLDNN, residual network, inception, LeNet, and DetectNet, it exhibits an improvement. The models' performance was evaluated using typical spectrum sensing measures. In the same grade of service, our model outperforms the competition in terms of detection probability and false alarm probability.

3. CONCLUSION

Other forms of signal classifiers and decision boundary algorithms that are less vulnerable to assaults, more resilient, and efficient for DSA are urgently needed. Most previous discoveries in the distributed detection literature that presume known to transmit signals cannot be directly applied to the cooperative sensing problem due to a lack of primary signal and channel information in cognitive radios. For machine learning algorithms, the time needed to perform the algorithm grows considerably as the number of samples for the detection/classification process increases. As a result, the difficulty of choosing acceptable algorithms may be viewed as a trade-off between accuracy and execution time.

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