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Survey on Machine Learning Based Cognitive Radio Implementation and Analysis

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ABSTRACT

Given that secondary users share the radios' frequency band, cognitive radio analysis is essential. The utilisation of the spectrum is improved via spectrum sensing and identification of the primary users inside the authorised spectrum. The principal users are referred to as licenced users. These major consumers don't always occupy the designated band. The frequency spectrum is then wasted as a result. In order to assign the band to secondary users during these periods, CR is employed. It is required to deploy cognitive radios (CR), which provide the potential feature of accessing the unused spectrum through dynamic spectrum management, because users of the licenced spectrum band only utilise a portion of their resources. Due to a lack of knowledge about a user's signal, a poor signal-to-noise ratio (SNR), and expensive expenses, user recognition is limited. This project's major goal is to get around these constraints. In this study, the identification of signal availability was accomplished using the cyclostationary feature and ensemble classifier. Since cyclostationary features perform better with signals with low SNR values, they are frequently employed. Additionally, these characteristics aid in determining the kind of modulation scheme and the existence of signal interference. In Octave, cyclostationary characteristics were derived from sample signals. It was possible to distinguish between the signal and noise by illustrating the FFTs of each. According to a study, cyclostationary spectrum detection is effective for detecting signals with low signal-to-noise ratios (SNR) levels. Standard ML techniques are the foundation of ensemble classifiers. Because ML produces better results than energy detection for signals with low SNR values, it is utilized in this situation.

Keywords: Machine Learning, Cognitive Radio, Cyclostationary Features, spectrum sensing,

1. Introduction

A 2002 evaluation by the Federal Communications Commission (FCC) found that spectrum access is a more pressing problem than real spectrum shortage. Due to numerous technological developments in the area of wireless communication, the already widespread use of 3G, 3.5G, 3.75G, and 4G technology, as well as the standardisation of MBMS, which has attracted significant market interest, the demand for Multimedia Broadcast and Multicast Services (MBMS) has significantly increased. Multimedia information requires more bandwidth, and since some applications and storage space have stringent delay requirements, there is an increasing need to make the most of the available spectrum.

Cognitive radio emerges as an enticing solution to the spectral congestion issue by providing the opportunistic use of frequency bands that are not generally occupied by licenced users as they cannot currently be utilised by users other than the licence owners. Energy-based detection, matching filter detection, cyclostationary feature detection, wavelet-based detection, and covariance-based detection are only a few of the spectrum sensing methods used in cognitive radio.

When the SNR of the signal is low, the energy detection technique has trouble. Due to the fact that matched filters increase the signal's SNR value, previous knowledge of the signal is required for matched filter detection to perform successfully under low SNR circumstances. The matching filter rapidly detects the spectrum, but it also requires synchronisation and specific details about the primary user, such as the modulation type, bandwidth, etc. The signals used in the digital communication system have distinctive statistical properties including double-sidedness and keying rate because of the sine wave carrier and symbol period. Such a signal has special characteristics called cyclostationary features.

It would be fascinating to investigate the idea of spectrum sensing and the detection of signal or noise to assign the bands. In this study, we suggested investigating Free Band sensing and allocation using machine learning methods. There is a huge demand for the radio spectrum that is now accessible due to the exponential rise of wireless services and applications. It has been proposed that a cognitive radio network (CRN) driven by artificial intelligence would be a more efficient approach to allocate the limited radio spectrum. By merging fog computing with various types of machine learning algorithms, the CRN framework may assess time-dependent signal data close to the signal source. Depending on the processing capability of the nebula node, various attributes and machine learning techniques are used to optimise the spectrum allocation.

There is a critical scarcity of unlicensed spectrum to fulfil the rising demand for wireless spectrum in this rapidly evolving digital age. More and more devices and applications rely heavily on the availability of illegal tapes. Underuse of authorised bands and congestion in unlicensed bands are diametrically opposite scenarios for these devices and applications. How well the channel is used will depend on how cellular services are expanded in the future. The problem of scarce radio spectrum can be solved with the use of cognitive radio (CR) networks.

2. Related Work

Cyclostationary feature detection is a technique used in wireless communication networks to identify the presence and absence of principal users. It is based on the observation that the signal structures of the majority of communication signals show underlying periodicities. The following authors have suggested this approach: Gardner (1991), Oner and Jondral (2004), Sutton et al. (2008), Cabric and Broderson (2005), Fehske et al. (2005), Ghozzi et al. (2006), Khambekar et al. (2007), Hou-Shin et al. (2007), Axell and Larsson (2011), Choi et al. (2007), Koivunen et al.

Utilising the cyclostationary properties of the received signals, the cyclostationary feature detection method may be used to identify wireless communications. This technique may be used to identify the particular set of characteristics of a particular radio signal for a certain wireless access system and performs well in low signal-to-noise ratio settings. To find the required signal, the cyclic spectrum of the received signal is measured, and the spectral correlation density function (SCD) is computed. A major user signal's spectral correlation peaks have been found using the cyclostationary feature detection approach, which may also be utilised to find sub-Nyquist cyclostationary features.

To enhance detection performance, cooperative cyclostationary spectrum sensing has also been suggested. Using cyclic detectors, this approach combines the binary judgements of secondary users, and the fusion centre and secondary users determine the best test thresholds. This method can discriminate between principal users, secondary users, and interference while being energy-efficient.

Cyclostationary feature detection has applications in signal categorization, modulation recognition, and signal fingerprinting in addition to spectrum sensing and main user detection.

The resilience of cyclostationary feature identification to noise and interference is one of its benefits. Even in low SNR and extremely congested settings, cyclostationary characteristics may be retrieved by taking use of the periodicity in the signal structure.

Cooperative spectrum sensing, in which many cognitive radios work together to enhance detection performance and minimise false alarms, can also employ cyclostationary feature detection.

The periodogram, the cyclic periodogram, the spectral coherence, and the cyclic correlation are a few techniques for calculating a signal's cyclic spectrum. Depending on the qualities of the signal and the statistics of the noise, each approach offers advantages and disadvantages.

Depending on the particular signal and modulation type, the choice of cyclostationary characteristics to be used for detection will vary. The cyclic autocorrelation and cyclic spectrum of the cyclic prefix, for instance, can be utilised as features for OFDM signals, whereas the cyclic autocorrelation and cyclic spectrum of the hopping sequence can be employed for frequency-hopping signals.

Cyclostationary feature detection has several drawbacks but can enhance detection effectiveness. For instance, it makes the cyclostationary assumption, which may not be accurate for all signals. Additionally, prior knowledge of the signal's properties, such as the kind of modulation and symbol rate, is necessary.

Extracting cyclostationary features involves identifying and characterizing the periodicity of the signal. Here are the steps to extract cyclostationary features:

- Autocorrelation Function: Calculate the autocorrelation function of the signal. The autocorrelation function gives you an idea of how the signal repeats over time.

Spectral Correlation Density: Calculate the spectral correlation density function. The spectral correlation density function gives you an idea of how the signal repeats over frequency.

- Cyclic Correlation Function: Calculate the cyclic correlation function. The cyclic correlation function gives you an idea of how the signal repeats over both time and frequency.
- Extract Features: Extract features from the cyclic correlation function. These features may include the frequency of the repeating pattern, the time delay between the repeating patterns, and the magnitude of the cyclic correlation function.

Once you have extracted the cyclostationary features, you can use them to differentiate signals. This can be done through pattern recognition algorithms such as machine learning techniques. You can train a classifier to recognize the cyclostationary features of different signals and use this classifier to classify new signals.

For example, suppose you want to differentiate between two types of modulated signals, AM and FM. You can extract cyclostationary features from each signal type and use them to train a classifier. The classifier can then be used to differentiate between AM and FM signals in new data.

2.1 Summary Paper

Name, Year and Reference	Summary
Hassaan Bin Ahmad, “Ensemble Classifier Based Spectrum Sensing in Cognitive Radio Networks”, Received 25 June 2018; Revised 23 September 2018; Accepted 10 December 2018; Published 1 January 2019	Explains cyclostationary features and shows the work flow of training and prediction phases using the ensemble classifier.
Prajwal Patil1, Pradeep R Pawar , Praneeth P Jain , Manoranjan K V , Devasis Pradhan, “Enhanced spectrum sensing based on Cyclo-stationary Feature Detection (CFD) in cognitive radio network using Fixed & Dynamic Thresholds Levels”, Received: 15.06.2020, Accepted: 22.06.2020, Published: 25.06.2020	Explains the enhanced spectrum sensing based on cyclostationary feature detection in cognitive radio with the use of fixed and dynamic thresholds.
Adigwe Wilfred and Okonkwo O.R., “A review of cyclostationary feature detection-based spectrum sensing technique in cognitive radio networks”, Accepted 10 February, 2016	Gives the review of cyclostationary feature detection-based spectrum sensing technique in cognitive radio networks.
Deep learning for spectrum sensing in cognitive radio , Surendra Solanki, Vasudev Dehalwar, Jaytrilok Choudhary, Published 17th January 2021	Proposes neural networks for AI based learning and hence spectrum sensing . Explains deep neural network model of spectrum sensing.

2.2Observation on Survey

As seen from the survey above, cyclostationary characteristics may be applied to spectrum sensing. The signal existing on the spectrum band can be detected using the cyclostationary properties. The pattern learning approach and other classifier types may then be used to discern between these characteristics.

We must first research the necessary criteria. The parts of the dataset are as follows: There are portions of noise and there is a signal. the earliest QPSK-based OFDM signals, which were 64-QAM, 16-QAM, and BPSK-based. The SNP variation spans the -5 dB to -15 dB range. The noise-only signals produced in the second stage are categorised as noise.

The signal was then divided into two pieces, and each piece was multiplied by the exponential of a complex number. Then, FFT was used on both sections. Following the discovery of the FFT connection between those two sections.

3. Conclusion

We investigated cognitive radio and put it into practise for spectrum sensing. Utilising the signal-available spectrum may be done via the cognitive radio approach. It is possible by detecting which band is free and which band is filled. The cyclostationary characteristics of the signal can be used to determine the band's state. It is possible to distinguish between the characteristics of noise and noise-signalling. These characteristics are subsequently used as input to train the ML model.

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