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ML Based Spectrum Sensing

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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.

Index Terms— Machine Learning, Cognitive Radio, Cyclostationary Features, spectrum sensing.

I. 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.

II. RELATED WORKS

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.

III. METHODOLOGY

1] Dataset Generation

This code generates a set of random signals with different modulation types, computes their cyclostationary features, adds noise to the signals, computes the cyclostationary features again, and saves the resulting features into an Excel file.

Let's break down the code step by step:

1. Importing the necessary libraries:

- `numpy` as `np`: Used for numerical computations and array operations.

- `scipy.signal` module: Provides signal processing functions, including correlation and chirp generation.

- `matplotlib.pyplot` as `plt`: Used for plotting.

2. Defining the `compute_cyclostationary_features` function:

- This function takes two parameters: `t` (time) and `x` (signal data).

- It computes the autocorrelation function (`Rxx`) using the `correlate` function from `scipy.signal`.

- It then computes the cyclic autocorrelation function (`CAF`) by iterating over a range of values (`m`) and calculating the mean of a portion of `Rxx` multiplied by its complex conjugate.

- The fundamental frequency (`f0`) is computed based on the range of `m` values and the length of the signal.

- Finally, the cyclic power spectral density (`MSF`) is calculated by iterating over `f0` values and summing the complex values of `CAF` multiplied by the exponential term.

3. Generating the signals:

- The code defines the number of signals (`num_signals`) and a list of modulation types (`modulation_types`).

- It creates an empty list (`arr`) to store the generated signal data.

- A loop iterates `num_signals` times to generate each signal.

- Inside the loop, a modulation type is randomly chosen from the `modulation_types` list.

- For each modulation type, a signal of length 1000 is generated.

- Depending on the modulation type, different modulation techniques are applied to the carrier signal (`carrier`) using the `modulating_signal` and additional random noise.

- The resulting signal is appended to the `arr` list.

4. Generating noise signals:

- Another loop generates 5000 noise signals.

- Each noise signal is generated using `np.random.normal` to generate a random signal with a mean of 0 and standard deviation of 1.

- The signal is then normalized by dividing it by its standard deviation.

- The normalized noise signals are stored in the `noise` list.

5. Computing cyclostationary features for the noise signals:

- Two empty lists (`MSF1` and `f01`) are created to store the computed features.

- A loop iterates over each noise signal in the `noise` list.

- For each noise signal, the `compute_cyclostationary_features` function is called, and the resulting features (`x` and `y`) are computed.

- An extra element of 0 is appended to `x` to match the length of the features from the original signals.

- The features are then added to the respective lists.

6. Saving the features to an Excel file:

- The `pandas` library is imported as `pd`.

- Two dataframes (`df1` and `df2`) are created from the original signal features (`MSF`) and noise signal features (`MSF1`), respectively.

- The dataframes are concatenated vertically (`axis=0`) to create a single dataframe (`df`).

- The resulting dataframe is saved to an Excel file named "output2.xlsx" using the `to_excel` function.

In summary, this code generates random signals with various modulation types, computes their cyclostationary features.

2] Neural Networks Model

This code uses the Keras library with TensorFlow backend to create a neural network model, train it on a dataset, and make predictions. Let's break down the code step by step:

1. Importing the necessary libraries:

- `pandas` as `pd`: Used for data manipulation and analysis.
- `numpy` as `np`: Used for numerical computations and array operations.
- `keras.models` module: Provides the `Sequential` model for creating neural networks.
- `keras.layers` module: Provides various types of layers (e.g., `Dense`, `Dropout`) used in neural networks.
- `sklearn.model_selection` module: Provides the `train_test_split` function for splitting the data into training and testing sets.
- `tensorflow` as `tf`: The backend library for Keras.

2. Checking for available GPUs:

- This code snippet checks if a GPU is available for use by TensorFlow.
- It lists the physical devices and sets TensorFlow to use the first GPU if available.
- The memory growth of the GPU is set to allow dynamic memory allocation.
- A message is printed indicating whether a GPU is being used or not.

3. Loading the data:

- The code reads an Excel file (`output (1).xlsx`) containing the data using the `pd.read_excel` function.
- The input features (`X`) are extracted from the first 500 columns of the dataframe.
- The output labels (`y`) are extracted from the 501st column of the dataframe.

4. Splitting the data into training and testing sets:

- The `train_test_split` function is used to divide the data into training and testing sets.
- The input features (`X`) and output labels (`y`) are split with a test size of 0.2 (20% of the data) and a random state of 42 for reproducibility.
- The resulting sets are assigned to `X_train`, `X_test`, `y_train`, and `y_test`.

5. Building the neural network model:

- A `Sequential` model is created using `model = Sequential ()`.
- Layers are added to the model using `model.add`.
- The first layer is a dense layer with 64 units and ReLU activation, taking the input dimension of 500.
- A dropout layer with a rate of 0.5 is added to prevent overfitting.p
- A second dense layer with 32 units and ReLU activation is added, followed by another dropout layer.
- The final layer is a dense layer with 1 unit and sigmoid activation for binary classification.

6. Compiling and training the model:

- The model is compiled with the binary cross-entropy loss function, Adam optimizer, and accuracy metric using `model.compile`.
- The model is trained on the training data (`X_train` and `y_train`) for 10 epochs with a batch size of 32 using `model.fit`.
- The validation data (`X_test` and `y_test`) is provided to evaluate the model's performance during training.

7. Evaluating the model:

- The model's performance is evaluated on the testing data using `model.evaluate`.
- The test loss and test accuracy are printed using `score [0]` and `score[1]`, respectively.

8. Making predictions:

- The code tries to predict the output for an `input_sample`, but it is not defined in the given code.

- The prediction is compared to 0.5 to determine the class label (0 or 1) using a ternary operator.

In summary, this code builds a neural network model using Keras, trains

it on a dataset, evaluates its performance, and makes predictions. It demonstrates a simple classification task with binary labels and showcases the steps involved in training a neural network model using Keras and TensorFlow.

IV. RESULTS AND ANALYSIS

We have used machine learning algorithms like the random forest, decision tree classifier, Bayes classifier, logistic regression, and neural network. The algorithms are compared depending on the accuracy and different performance factors.

In case of signal classification there are 2 output class signal and noise. Among all the algorithms Neural Network and Random Forest has obtained the highest training accuracy 1 and testing accuracy as 1.

TABLE I

COMPARISON OF ALGORITHMS

Algorithm	Accuracy
Logistic Regression	0.86375
Decision Tree	0.74
Random Forest	1
SVM	0.8745
Naive Bayes	0.8745
Neural Network	1

V. CONCLUSIONS

In this paper the algorithm for dataset generation of spectrum sensing is explained. The model that uses the same dataset for classifying the signal and noise is also presented. The dataset contains signal values from different modulation techniques and wide range of SNR values. The cyclostationary features were of those signals were extracted and were the input features of the model. A neural network model is used here, with five hidden layers. There are two output classes signal and noise in which the input data has been classified. Lastly comparison of the different ML algorithms is shown to give us an idea for their performances respectively.

REFERENCES

[1] 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

[2] 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

[3] Adigwe Wilfred and Okonkwo O.R., “A review of cyclostationary feature detection-based spectrum sensing technique in cognitive radio networks”, Accepted 10 February, 2016

[4] ANALYSIS OF SPECTRUM SENSING TECHNIQUES IN COGNITIVE RADIO Abdul Razaq, Muhammad Riaz and Anas Bilal

[5] Cognitive Radio Principles and Spectrum Sensing J. Divya lakshmi, Rangaiah. L International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249-8958 (Online), Volume-8 Issue-6, August 2019

[6] Deep learning for spectrum sensing in cognitive radio, Surendra Solanki, Vasudev Dehalwar, Jaytrilok Choudhary, Published 17th January 2021

[7] Cabric, D.; Mishra, S.M.; Brodersen, R.W. Implementation issues in spectrum sensing for cognitive radios. In Proceedings of the Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, Pacific Grove, CA, USA, 7–10 November 2004; Volume 1, pp. 772–776.

[8] Marcus, M.J. Spectrum policy for radio spectrum access. Proc. IEEE 2012, 100, 1685–1691. [CrossRef]

[9] Mitola, J.; Maguire, G.Q. Cognitive radio: Making software radios more personal. IEEE Pers. Commun. 1999, 6, 13–18.

[10] Gao, J.; Yi, X.; Zhong, C.; Chen, X.; Zhang, Z. Deep Learning for Spectrum Sensing. IEEE Wirel. Commun. Lett. 2019, 8, 1727–1730.

[11] Cheng, Q.; Shi, Z.; Nguyen, D.N.; Dutkiewicz, E. Sensing OFDM Signal: A Deep Learning Approach. IEEE Trans. Commun. 2019, 67, 7785–7798.