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Automatic Modulation Classification for Cognitive Radio

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ABSTRACT: Cognitive Radios have become a key research area in communications over the past few years. They play an important role in dynamic spectrum management and interference identification.Automatic Modulation Classification is the automatic recognition of the modulation format of a sensed signal. Most modulated signals exhibit the property of Cyclostationarity that can be exploited for the purpose of classification. A feature-based method called Cyclostationary Feature Detection is able to classify different modulation schemes. TheSpectral Correlation Function obtained from the sensed signal is used as a cyclic feature. The Cycle frequency Domain Profile derived from Spectral Correlation Function is used as a discriminator in the classification process since several modulation schemes have unique cycle frequency domain profiles. The neural network approach based on the learning mechanism is employed for pattern matching. It is used for classification of data patterns and distinguishing them into predefined set of classes.The two layered neural network is trained using the Back Propagation Algorithm.

KEYWORDS: Cognitive Radio; Cyclostationarity Feature Detection; Spectral Correlation Function; Cyclic Domain Profile; Neural Networks; Back Propagation Algorithm.

I. INTRODUCTION

Modulation is the process of varying a periodic waveform in order to use that signal to convey a message. The purpose of AMC algorithms in a radio receiver is to identify the existence of a signal in a particular frequency band at a given location at a given time and then determine the modulation type being employed in the spectrum. For the receiver, AMC is the intermediate step between signal detection and demodulation. AMC plays an important role in dynamic spectrum management and interference identification for civilian, commercialand military applications. The popularity of Software Defined Radio and Cognitive Radio technologies is increasing over past few decades. AMC is often a critical issue when there is no prior knowledge about signal power, carrier frequency etc. [2].

The main contribution among many automatic modulation classificationalgorithms is based on cyclostationary feature detection method. This feature extracting algorithm can be used with classifier such as Neural Network. Signal detection and signal classification based on pattern matching algorithm becomes robust using cyclostationarity of signals. Neural networks are helpfulfor modulation classification when i) the carrier signal and bandwidth are unknown and ii) the interfering signals and noise are in considerably effective [5].

II. RELATED WORK

In [1], the author has introduced a spectral correlation theory for cyclostationary time series.Second order periodicity of the signal is exploitedusing cyclostationary properties. A large number ofautomatic modulation classification methods have been developedtill today from the researchof at least two decades.Some modulation classification algorithms are based on the use of signal cyclostationarity that falls under the category of feature based methods [2]. A brief survey of the literature on cyclostationarity and the applications ofcyclostationarity in communication, signal processing and many other research areas are described in [3].The authors in [4] have usedthe cycle frequency domain profile (CDP) for signal detection and Hidden Markov Model (HMM) for signal classification to process extracted signal features due to its strongpattern-matching capability. The definitions of Spectral Coherence and Cycle Frequency Domain Profile are mathematically explained. In [5] and [6], the authors have presented signal classification using cyclic spectral analysisand the simulation results of different modulation types under various noise conditions.In [8] and [9], the authors have discussed the basics of neural networks, their classification and applications in pattern

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recognition.The objective of paper [10] and [11] is to summarize the methods used in various stages of a pattern recognition system andadvantages of Back Propagation Algorithm over other techniques to recognize the complex patterns along with other real-life applications. The authors have given the overview of Artificial Neural Network, its working principle and training in [12] and [13].In [14], the author has provided comprehensive fundamentals in detailed manner with examples and computer-oriented experiments. Moreover, the concepts associated with neural networks are explained. The mathematical treatment of layered neural networks is given in detail.In [15], the author has introduced supervised learning algorithm named Scaled Conjugate Gradient (SCG) andits performanceis compared to that of standard Back-Propagation Algorithm. According to [16], the spectral correlation analysis can be preferably applied for signals that are produced by some periodic modification or modulation of stationary random noise. In [17], the author investigates the spectral features of several basic analog and digital modulated signals from point view of modulation recognition and parameter estimation.In [18] and [19], the spectral correlation function that is a generalization of the power spectral density function is described. Explicit formulae for the spectral correlation function for various types of analog and digital modulated signals are also derived.

III. PROPOSED ALGORITHM

A. *Design Considerations:*

- Channel is assumed to be noisy with AWGN with varying values of standard deviation.
- Number of data symbols are 2000 and symbol rate is 3 GHz.
- Sampling frequency selected satisfied Nyquist criterion.
- FFT is used for time smoothing.
- Raised Cosine filter is used for frequency smoothing.
- 400 CDPs of different modulation schemes are input to the neural network.
- Number of hidden neurons is 10.

B. *Description of the Proposed Algorithm:*

Aim of the proposed algorithm is to obtain the SpectralCorrelation Function (SCF) and Spectral Coherence (SC). The transmitter selects one of the four modulation schemes demonstrated here to transmit a stream of data bits. The receiver, upon receiving the signal, extracts its cyclostationary features (spectral coherence function and cyclic domain profile) and uses a trained neural network classifier to classify the modulation scheme. The proposed algorithm consists of following steps.

Step 1:Divide the incoming modulated signal into N frames.
Step 2:Take the Fourier transform of each frame.
Step 3:Shift the FFT of each frame by (+α/2) and (-α/2) and multiply them.
Step 4:Take the average value of all the N frames.
Step 5:Perform frequency smoothening.
Step 6:Repeat the operation from Step 2 for each value of alpha to obtain SCF.

$$S_{xT}^{\alpha}(f) = \frac{1}{T} X_T\left(t, f + \frac{\alpha}{2}\right) X_T^{*}\left(t, f - \frac{\alpha}{2}\right) \qquad - \ (1)$$

Step 7:Normalize the SCF to obtain SC.

$$C_x^{\alpha}(f) \triangleq \frac{S_x^{\alpha}(f)}{[S(f + \alpha/2)S(f - \alpha/2)]^{1/2}} \qquad - \ (2)$$

However the use of SC requires large amount of data and hence we use only the peak values in the SC. These peak values are called as cyclic frequency domain profile (CDP) or α-profile.

$$I(\alpha) \triangleq \max_{f} |C_x^{\alpha}(f)| \qquad - \ (3)$$

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IV. PSEUDO ALGORITHM

Step 1: Receive the noisy modulated signal.
Step 2: Obtain its Cyclic Periodogram.
Step 3: Perform Time Smoothing.
Step 4: Perform Frequency Smoothing.
Step 5: Obtain Spectral Coherence.
Step 6: Obtain Cyclic Domain Profile.
Step 7: Train the Neural network with various CDP patterns.
Step 8: Obtain Classification Confusion Matrix.
Step 9: Verify the results for different modulation schemes.

V. SIMULATION RESULTS

The proposed algorithm is simulated with combined use ofLabVIEW and MATLAB. If the received signal consists of only noise (assumed AWGN for simulation), then the SCF as well as CDP plots do not show presence of any peak, thereby indicating the absence of signal in the sensed channel i.e. the absence of the primary user.

If the sensed signal is BPSK modulated, then there are three distinct peaks along α axis, as shown in Fig. 1 and Fig. 2. The first peak corresponds to the symbol rate f_r, the second one corresponds to the carrier frequency f_c and the last one corresponds to fc + f_r.

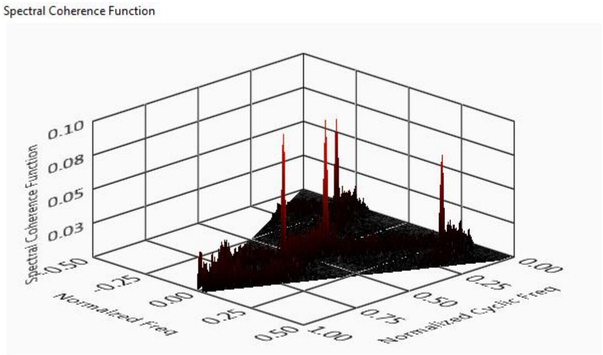

Fig. 1: SCF for BPSK

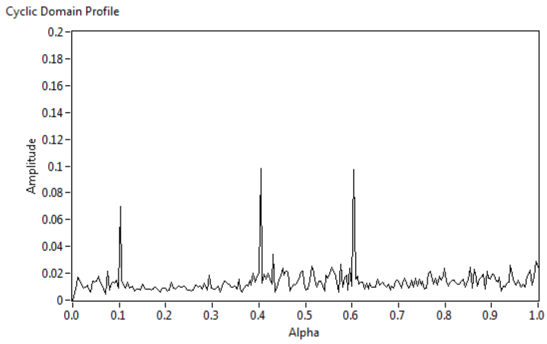

Fig. 2:CDP for BPSK

If the sensed signal is QPSK modulated, there is only one peak along α axis, which corresponds to the symbol rate f_r as shown in Fig. 3 and Fig. 4. The extra two peaks in BPSK are missing in QPSK, because, QPSK is a balanced modulation (has both in phase and quadrature) and hence peaks corresponding to the carrier frequency get cancelled out.

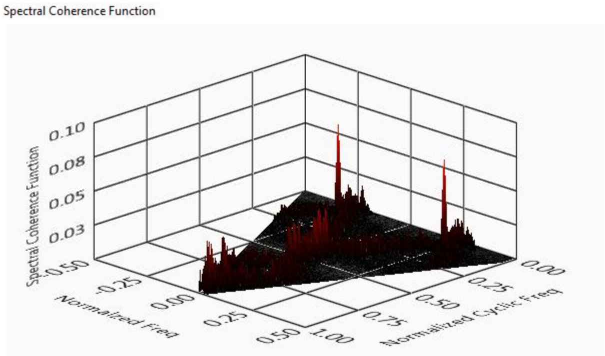

Fig. 3: SCF for QPSK

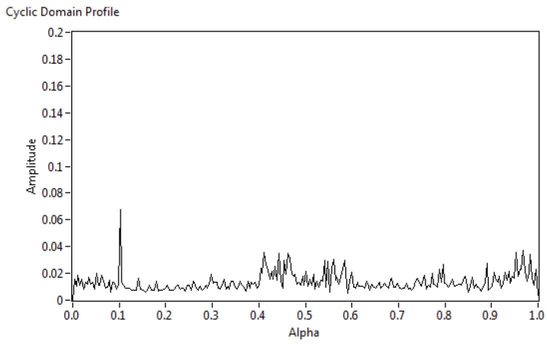

Fig. 4:CDP for QPSK

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If the sensed signal is FSK modulated, there are two impulses in the CDP as shown in Fig. 5 andFig. 6, which correspond to two carrier frequencies involved, i.e. 'mark' frequency and 'space' frequency. Also, the two peaks that overlap the two impulses are observed. These two peaks along with the third one are analogous to the same observed in CDP of BPSK.

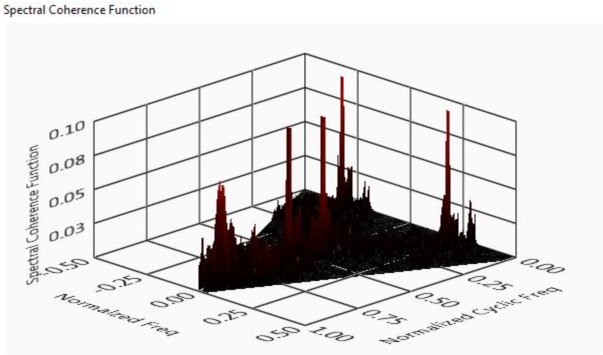

Fig. 5: SCF for FSK

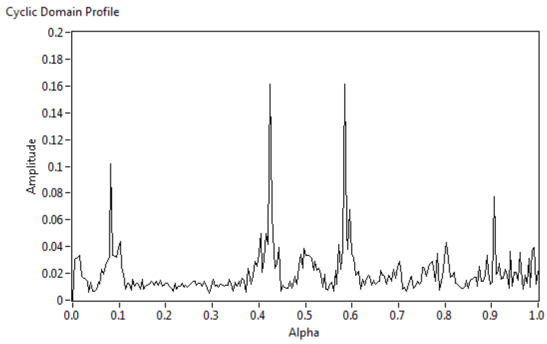

Fig. 6:CDP for FSK

If the sensed signal is MSK modulated, only two peaks are observed in the CDP as shown in Fig. 7 andFig.8, which correspond to the two quadrature carriers $\sin 2\pi f_c t$ and $\cos 2\pi f_c t$.

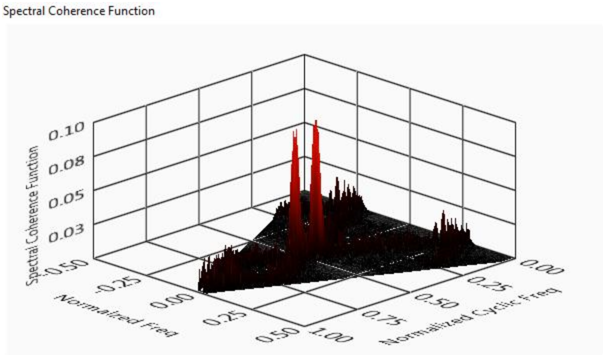

Fig. 7: SCF for MSK

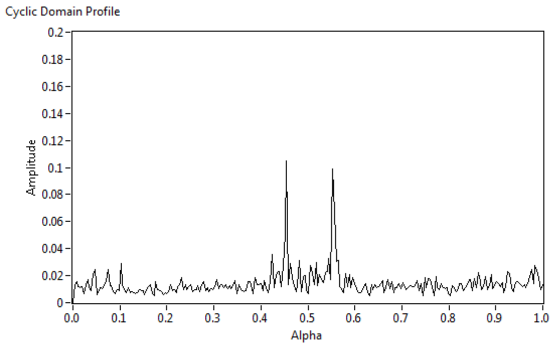

Fig. 8:CDP for MSK

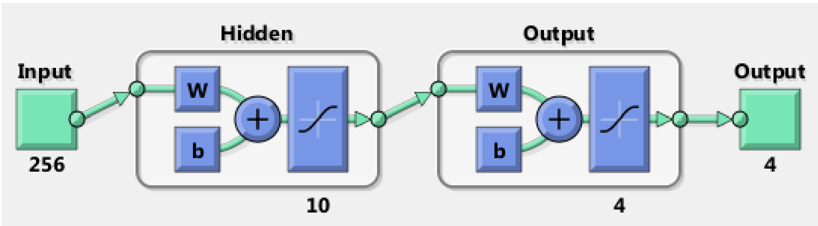

Fig. 9: Neural Network trained using 256 point CDPs

Fig. 10 shows a plot of mean square error versus number of training iterations (epochs) according to which the best validation performance is 0.00026501 at epoch 36. It can be concluded from the plot that the mean square error decreases with increase in number of epochs and attains a stable value at some instant.

Fig. 11 is called Classification Confusion Matrix for training, validation, testing as well as overall classification result. It shows the various types of errors that occurred for the final trained network. In other words, it represents the accuracy of classification.The diagonal cells show the number of cases that were correctly classified (in green) and the off-diagonal cells show the misclassified cases (in red). The blue cell in the bottom right shows the total percentage of correctly classified cases and the total percent of misclassified cases. For training, the accuracy achieved is 98.9%, for

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testing, it is 98.3% and for validation, it is 100%. The results show very good recognition since overall accuracy of all confusion matrix is 99%.

Thus, the network performs exceptionally well, even at low SNR levels.

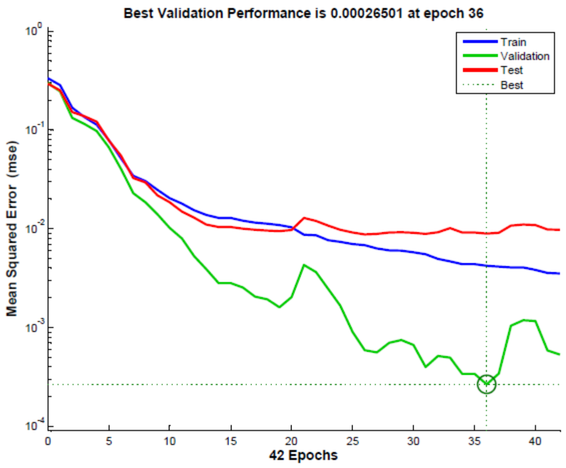

Fig. 10: Training, Validation and Test Performance Plot

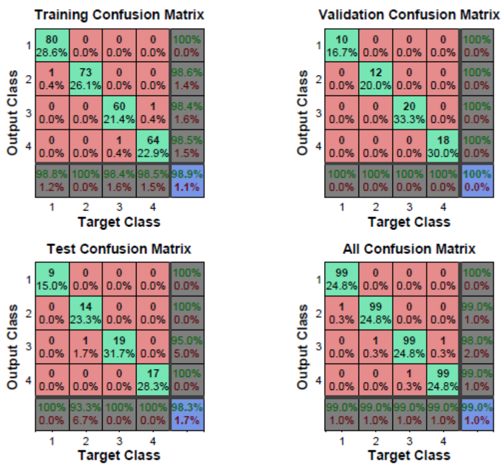

Fig. 11: Classification Confusion Matrix

VI. CONCLUSION AND FUTURE WORK

The simulation results showed that the combination of the SCF algorithm with the trained neural network performs accurately.The CDP can be used as a good discriminator of modulation schemes, because of the uniqueness in their CDP patterns. Using this cyclostationarity based AMC algorithm, signal modulation types can be determined quickly and reliably.The results show very good recognition since overall accuracy of all confusion matrix is 99%.The proposed system performs exceptionally well evenat low SNR levels.Automatic Modulation Classification not only gives the assurance of the presence of signal by detecting its scheme of modulation but also helps to demodulate the signal by knowing its type.As the performance of the proposed algorithm is analyzed with thelimited number of modulation schemes, in future some more modulation schemes can be takeninto consideration. Further, using a neural network for classification constitutes a highly flexible method, since the network can be retrained in order to incorporate new signal modulation types. Performance of this cyclic spectrum based AMC system is tested in a stationary noise environment such as AWGN channel. The AMC should also be tested in a fading channel environment with noise uncertainty and for more sophisticated modulation schemes such as OFDM, DVB and many more.

REFERENCES

[1] W. A. Gardner, “The spectral correlation theory of cyclostationary time-series”, Signal Processing, vol.11, no.1, pp. 13-36, 1986.
[2] B. Ramkumar, “Automatic Modulation Classification for Cognitive Radios using Cyclic Feature Detection”, IEEE Circuits and Systems Magazine, Volume: 9, Issue: 2, Pages: 27-45, 2009.
[3] W. A. Gardner et al., “Cyclostationarity: Half a century of research”, Signal Processing 86, Pg. 639–697, 2006.
[4] K. Kim, I. A. Akbar, K. K. Bae, J.-S. Um, C. M. Spooner, and J. H. Reed, “Cyclostationary approaches to signal detection and classification in cognitive radio,” in Proc. IEEE DySpan, Pg. 212–215, 2007.
[5] A. Fehske, J. Geaddert, and J. H. Reed, “A new approach to signal classification using spectral correlation and neural networks,” in Proc. IEEE Int. Symp. New Frontiers in DySpan, 2005.
[6] Aparna P.S., M. Jayasheela, “Cyclostationary feature detection in cognitive radio using different modulation schemes”, International Journal of Computer Applications, vol. 47, No.21, Pg. 12-16, 2012.
[7] F. Hameed, O. A. Dobre, D. C. Popescu, “On the Likelihood-Based Approach to Modulation Classification”, IEEE transactions on wireless communications, vol. 8, no. 12, Pg. 5884-5892, 2009.
[8] Andrej Krenker et al., “Introduction to the Artificial Neural Networks”, Artificial Neural Networks - Methodological Advances and Biomedical Applications, 2011.
[9] B. Yegnanarayana, “Artificial neural networks for pattern recognition”, 1994.
[10] Dr. Rama Kishore and TaranjitKaur, “Backpropagation Algorithm: An Artificial Neural Network Approach for Pattern Recognition” IJSER, 2012.
[11] TaranjitKaur, “Implementation of Backpropagation Algorithm - A Neural Network Approach for Pattern Recognition” IJERD, 2012.
[12] S. B. Maind et al., “Research Paper on Basic of Artificial Neural Network” IJRITCC, 2014.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

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[13] Vidushi Sharma et al., "A Comprehensive Study of Artificial Neural Networks", IJARCSSE, 2012.
[14] Simon Haykin, "Neural Networks-A Comprehensive Foundation", 2nd Edition, 1999.
[15] M. F. Moller, "A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning", Neural Networks, Vol. 6, 1993, Pg. 525-533, 1991.
[16] J. Goerlich et al., "Signal Analysis Using Spectral Correlation Measurement", IEEE Instrumentation and Measurement Technology Conference, Pg. 1313-1318, 1998.
[17] Hong Wang, "Spectral Correlation Function of Basic Analog and Digital Modulated Signals", IEEE, School of Electronic Engineering, University of Electronic Science and Technology of China, 2013.
[18] W.A. Gardner, "Spectral Correlation of Modulated Signals: PART I - Analog Modulation", IEEE Trans. on Communication, vol. 35, pp. 584-594, 1987.
[19] W.A. Gardner, "Spectral Correlation of Modulated Signals: PART II - Digital Modulation", IEEE Trans. on Communication, vol.35, pp. 595-601, 1987.