



Available Online through

www.ijptonline.com

AUTOMATED DIGITAL SIGNAL CLASSIFICATION FOR COGNITIVE RADIO SYSTEMS USING TEMPORAL AND SPECTRAL FEATURES

M.Bhuvaneshwari¹, S.Srinivasa Rao Madane²

¹Associate Professor, Department of Electronics and Communication Engineering,
Indra Ganesan College of Engineering, Tamilnadu.

²Principal, Department of Computer Science Engineering, Adhi Parasakthi College of Engineering, Tamilnadu.

Email: bhuvaneshwarianna.phd@gmail.com

Received on: 03-02-2017

Accepted on: 12-03-2017

Abstract:

In this paper, an efficient approach for automated signal classification is presented for use in a cognitive radio system. The proposed system uses temporal and spectral features for efficient classification. In order to obtain spectral features, the Empirical Mode Decomposition (EMD) is used to decompose the given signal. From the Intrinsic Mode Functions (IMF), spectral features such as spectral centroid, coefficient of variation and the spectral skew are extracted. Also, temporal features such as mean, variance and skewness are extracted from the modulated signal. Both temporal and spectral features are combined and K Nearest Neighbour (KNN) classifier is used to classify the signal. The proposed system is designed to identify three different digital modulation schemes; Phase Shift Keying (PSK), Differential PSK (DPSK) and Quadrature Amplitude Modulation (QAM). Results show that the temporal and spectral features provides an overall accuracy of 99.3% (10 dB), 97.6% (5 dB), 84% (1 dB), and 54.3% (0 dB).

Key words: Cognitive radio, digital signal classification, modulation, spectral features, KNN classifier.

1. Introduction

Software Defined Radio (SDR) is defined as: "Radio in which some of the physical layer functions are software defined". It requires the type of modulation of received signal. To achieve this, many algorithms are developed recently. The classification of analog and digital signals using Support Vector Machine (SVM) is presented in [1]. Seven different modulation schemes are used to detect the signals. A set of eighteen features; twelve statistical features and six spectral features are used for the classification. A review for cognitive radio using SDR design is explained in [2] including coder-decoder adaptations, frequency hopped spread spectrum modulation and demodulation technique to maintain the binary encoded representation and offset quadrature phase shift keying.

The primary radio signals are sensed in a cognitive radio environment for automatic modulation classification is presented in [3]. The four salient key features can easily differentiate the noise from a signal. Four signals (2ASK, 4ASK, BPSK and QPSK) are used with amplitude information and one signal (2FSK) without amplitude information. Four cyclostationary feature are used and fed to neural network for classification. An analysis for automatic modulation classification using cyclic feature for cognitive radios is discussed in [4]. It consists of several modulation signals like PSK, PAM, QAM and BPSK. The classification based on cyclic spectrum, hidden Markov models, cumulants, and neural network are explained.

A review of fractional lower order statistics based automatic modulation classification using cumulants for cognitive radios is discussed in [5]. It adopts a pattern recognition based approach for classification based on fourth order cumulants which consist of fractional lower order statistics. The digital signal classification based on second order statistical approach is defined in [6]. The modulated signals are transferred via Additive White Gaussian Noise (AWGN) and Rayleigh channel. Three modulation schemes are employed such as DPSK, PSK and MSK. The complex envelopes for real and imaginary part in 2nd order cumulants is extracted and these statistical features are applied to SVM classifier.

A review for signal classification based on fuzzy logic is described in [7]. The extraction of bandwidth and center frequency from the power spectral density is used as features. The classification is based on implicit signal features, explicit features and also the fusion of both features. Digital signal classification based on cyclostationary feature in cognitive radio is explained in [8].

Four modulation schemes such as BPSK, QPSK, FSK and MSK are used. SVM, linear discriminant analysis, neural network, KNN, neuro-fuzzy classifier and naïve Bayes are used.

A method for automatic modulation classification approached by Likelihood-Ratio test (LRT) is explained in [9]. It studies various classification solutions derived from likelihood ratio test, and discusses the detailed characteristics associated with all major algorithms. Multiuser automatic modulation technique based on distributed sensing in multipath fading channels for cognitive radios is described in [10]. It classifies signals transmitted by multiple users using fourth order cumulants.

In this paper, an efficient approach for digital signal classification in cognitive radio is presented. The rest of the paper is organized as follows. Section 2 gives the methods and material used by the proposed digital signal classification. The results obtained are discussed in section 3 and the conclusions are described in section 4.

2. Methods and Materials

The main objective of the proposed digital signal classification system is to find the modulation technique of the transmitted signal. The two different stages; feature extraction stage and classification stage are involved in the design of the proposed signal classification system. Figure 1 shows the overall automated system for the classification of modulated signal.

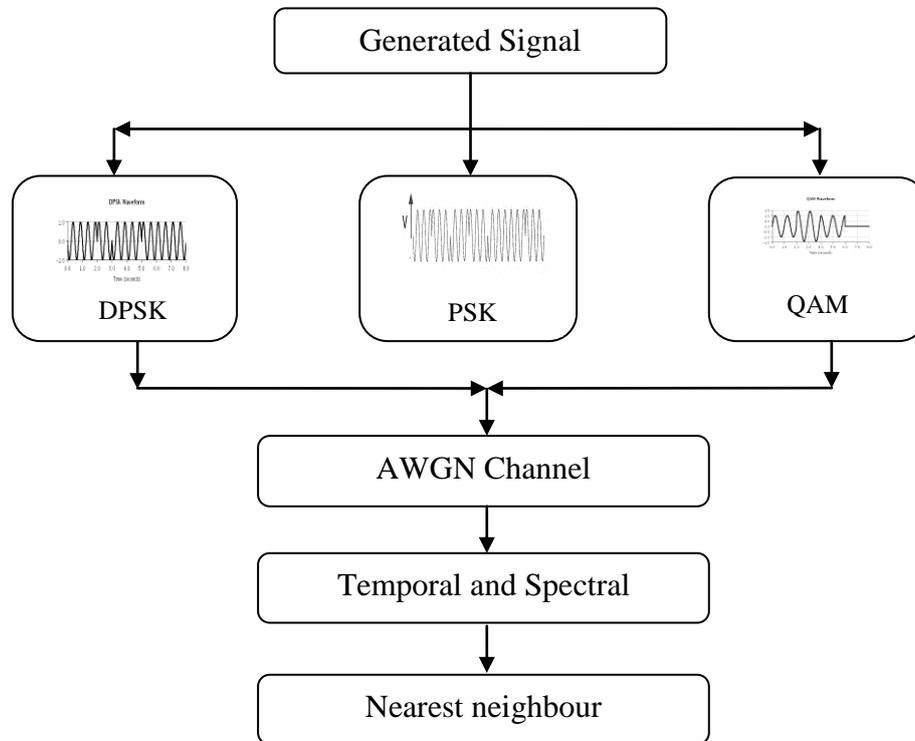


Figure 1 Proposed signal classification system using temporal and spectral features.

In feature extraction, a set of features that best describes the information content of the modulated signal is computed. The temporal and spectral features are computed for each training modulated signal and used as features for the corresponding signal. This method is applied to all training signals with different modulation. Then, the extracted features with their corresponding modulation types are stored for further processing. The next step in the proposed system is the design of a classifier system to identify the modulation technique. The proposed system uses nearest neighbour classifier for the classification.

2.1 Feature Extraction

The proposed system uses temporal and spectral features for the classification. These features are extracted in the feature extraction stage. Temporal features includes: mean, variance, skew and spectral features include spectral centroid, coefficient of variation and the spectral skew of the IMFs. The IMFs are obtained as a result of the application of EMD on the modulated signal. Three digital modulation schemes: DPSK, PSK4, 64QAM are analyzed in this study.

2.1.1 Temporal Features

Temporal features provide the characteristics of distribution of samples such as asymmetry, dispersion around the mean and concentration of data. The following equations are used to obtain the temporal features.

$$\text{mean}(\mu_t) = \frac{1}{N} \sum_{i=1}^N y_i \quad (1)$$

$$\text{variance}(\sigma_t) = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \mu_t)^2} \quad (2)$$

$$\text{skewness}(\beta_t) = \frac{1}{N} \sum_{i=1}^N \left(\frac{y_i - \mu_t}{\sigma_t} \right)^3 \quad (3)$$

where N is the number of samples.

2.1.2 Spectral Features

The decomposition of a signal by EMD and IMFs provides a number of oscillatory components in a data dependent [11]. These components satisfy the following two conditions; the number of extreme or zero crossings must be the same or differ by at most one and the local maxima and the local minima are defined as the average value of the envelope at any point is zero. The procedure for calculating IMFs for a given signal $x(t)$ is as follows:

1. Find maxima and minima in $x(t)$.
2. Generating the envelopes $e_l(t)$ and $e_m(t)$ while interpolate between minima and maxima.
3. Find out the local mean as $a(t) = \frac{e_m(t) + e_l(t)}{2}$.
4. Extract $h_1(t) = x(t) - a(t)$.
5. Determine whether $h_1(t)$ is an IMF or not based on two conditions is mentioned above.
6. Repeat step 1 to 4 until an IMF is obtained.

A residual signal $r_1(t) = x(t) - c_1(t)$ is obtained which is treated as the next signal. This process can be repeated in order to get the final residue. No more IMFS while decomposing the final residue. The original signal can be defined by the obtained residues is as follows:

$$x(t) = \sum_{m=1}^M c_m(t) + r_M(t)$$

where M is the number of IMFs, $c_m(t)$ is the m^{th} IMF and $r_M(t)$ is the final residue. From the IMFs, the following features; spectral centroid, spectral skew and variation coefficient are extracted and used along with the temporal features for the classification. Table 1 shows the extracted spectral features from the IMFs.

Table 1 Spectral Features used in this study.

Spectral Features	Formula
spectral centroid	$C_s = \frac{\sum_{\omega} \omega P(\omega)}{\sum_{\omega} P(\omega)}$
spectral skew	$\beta_s = \frac{\sum_{\omega} \left(\frac{\omega - C_s}{\sigma_s} \right)^3 P(\omega)}{\sum_{\omega} P(\omega)}$
variation coefficient	$\sigma_s^2 = \frac{\sum_{\omega} (\omega - C_s)^2 P(\omega)}{\sum_{\omega} P(\omega)}$
Where $P(\omega)$ is the amplitude of ω^{th} frequency bin in the spectrum	

For all transmitted signal, temporal and spectral features are extracted using the formulae in this section and stored in the database for the classification modulation techniques using KNN classifier [12].

2.2 Classification

The final step in the proposed system is the classification where the given signal is classified into one of the three digital modulation schemes: DPSK, PSK4, 64QAM are analyzed in this study. For classification, KNN classifier is used.

The proposed features are extracted for the unknown signal and given as an input to the KNN classifier along with the database already obtained in the feature extraction stage. Commonly used Euclidean distance measure is used for classification based on the distance between the features of unknown signal and the training features in the database.

3. Results and Discussions

In this section, the classification results obtained by the proposed signal classification system outlined in the previous section are discussed.

To analyze the performance 400 signals are generated and modulated using three modulation schemes; DPSK, PSK4, 64QAM. They are transmitted through AWGN channel with 0dB, 1dB, 5 dB, and 10dB noise density. Using temporal and spectral features with KNN classifier, the modulation of the signals are classified. 300 signals are used for training and 100 signals are tested with KNN classifier. The following Tables 2 to 5 show the confusion matrix obtained by the system.

Table 2 Confusion matrix at 0 dB SNR using KNN classifier

Modulation Type	DPSK	PSK4	QAM 64
DPSK	54	45	8
PSK4	35	49	32
QAM 64	11	6	60

Table 3 Confusion matrix at 1 dB SNR using KNN classifier

Modulation Type	DPSK	PSK4	QAM 64
DPSK	85	15	4
PSK4	12	80	9
QAM 64	3	5	87

Table 4 Confusion matrix at 5 dB SNR using KNN classifier

Modulation Type	DPSK	PSK4	QAM 64
DPSK	97	2	2
PSK4	2	98	0
QAM 64	1	0	98

Table 5 Confusion matrix at 10 dB SNR using KNN classifier

Modulation Type	DPSK	PSK4	QAM 64
DPSK	99	1	0
PSK4	1	99	0
QAM 64	0	0	100

It is observed from the obtained results that the proposed temporal and spectral features provides promising results with an overall accuracy of 99.3% (10 dB), 97.6% (5 dB), 84% (1 dB), and 54.3% (0 dB). Figure 2 shows the obtained accuracy of the proposed system at various noise densities.

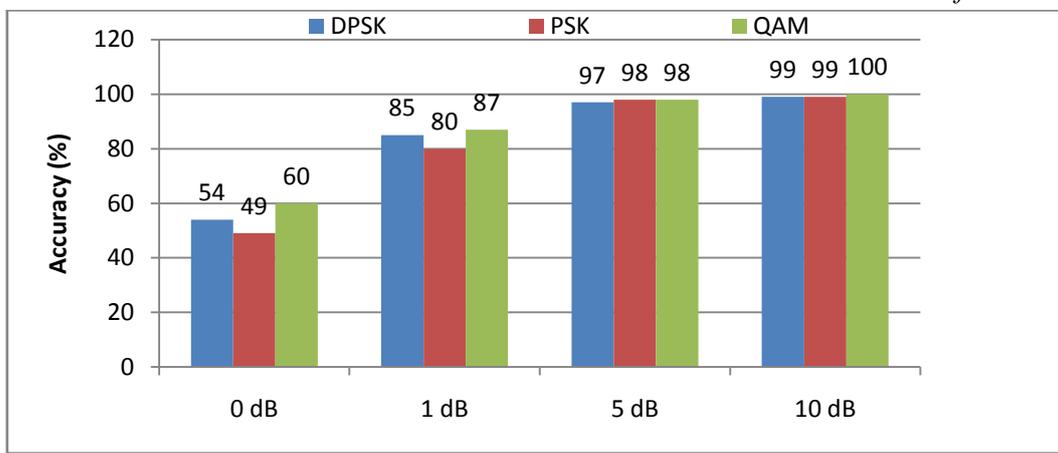


Figure 2 Classification accuracy of the proposed signal classification system.

4. Conclusion

An efficient approach for digital signal classification using temporal and spectral features is presented in this study. Temporal features are directly extracted from the modulated signal and spectral features are extracted from the IMFs of the modulated signal obtained from the EMD procedure. Three modulation schemes are analyzed using KNN classifier. From the experimental results, it is inferred that the combination of temporal and spectral features provides better performance.

References

1. Marina Petrova, Petri M ah onen & Alfredo Osuna. **Multi-Class Classification of Analog and Digital Signals in Cognitive Radios using Support Vector Machines**, 978-1-4244-6317-6/10/\$26.00 © 2010 IEEE.
2. Rajeshree D. Raut & Dr. Kishore D. Kulat. **SDR Design for Cognitive Radio**. 978-1-4577-0005-7/11/\$26.00 ©2011 IEEE.
3. Barathram Ramkumar. **Automatic Modulation Classification for Cognitive Radios Using Cyclic Feature Detection**. 1531-636X/09/\$25.00©2009 IEEE .
4. Jide Julius Popoola & Rex van Olst. **Application of neural network for sensing primary radio signals in a cognitive radio environment**. IEEE - 978-1-61284-993-5/11/\$26.00 ©2011 IEEE 13 - 15 September 2011.
5. Narendar1, M., Vinod, A.P., Madhukumar, A.S. & Anoop Kumar Krishna. **Automatic Modulation Classification for Cognitive Radios using Cumulants based on Fractional Lower Order Statistics**, 978-1-4244-6051-9/11/\$26.00 ©2011 IEEE.
6. Kaleem Ahmed, Uwe Meier & Halina Kwasnicka. **Fuzzy logic based signal classification with cognitive radios for standard wireless Technologies**. 10.4108/ICST.CROWNCOM2010.9239.

7. Jefferson L. Xu, Wei Su & MengChu Zhou,' Software-Defined Radio Equipped With Rapid Modulation Recognition', IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, VOL. 59, NO. 4, MAY 2010.
8. Kannan, R. & Ravi, S. Classification of Digital Signals in Cognitive Radio Based on Second-Order Statistical Approach. 978-1-4673-4634-4/12/\$31.00 ©2012 IEEE.
9. Jefferson L. Xu, Wei Su & Mengchu Zhou. Likelihood-Ratio Approaches to Automatic Modulation Classification. IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART C: APPLICATIONS AND REVIEWS, 41 (4), JULY 2011.
10. Munawwar M. Sohal, Barathram Ramkumar & Tamal Bos. Multiuser Automatic Modulation Classification for Cognitive Radios using Distributed Sensing in Multipath Fading Channels. 978-1-936968-8©2012 ICST.
11. Farhan Riaz, et al, "EMD based Temporal and Spectral Features for the Classification of EEG Signals Using Supervised Learning" IEEE Transactions on Neural Systems and Rehabilitation Engineering vol. 24, no.1, pp-28-35,2016
12. Kannan, R. & Ravi, S. Multiresolution Analysis for Digital Signals Classification Based on DWT. Journal of Computer Applications (JCA) ISSN: 0974-1925, Volume 5, Issue 4, 2012.