Automatic Digital Modulation Recognition using Artificial Neural Network in Cognitive radio

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Abstract: Wireless technology is increasing rapidly over the last two decades. It has been limited to growth in a wireless radio spectrum, because the radio spectrum is finite resource which indicates that there is significant scope of improving spectrum utilization. Cognitive radio (CR) is key enabling technology that improves the efficiency of spectrum utilization. The spectrum sensing gives the capability of CR to detect there is no primary user (PU) present in the band over wireless fading channel. In this paper we study multi-class digital classification based on automatic modulation recognition through the Artificial Neural Network (ANN). Implement and design 8 digital modulations are: 2ASK, 2FSK, 4ASK, 4FSK, 2PSK, 4PSK, DPSK, and 16QAM. They widely used and best known in the recent communication systems. The maximum value of spectral density of normalized centered amplitude and the average value of normalized absolute centered instantaneous phase deviation choose as key features for digital modulation recognizer based on the ANN. We used the multipath fading channel to model signals propagation and corrupted the signals by Additive White Gaussian Noise (AWGN) for testing the algorithm. The simulation results show that the ANN could be be recognized the different types of the PUs and corrected classify the signals in its current state of development.

Keywords: Cognitive Radio, Digital Modulation, ANN, Multipath Fading Channel.

1. INTRODUCTION

Wireless technology is growing rapidly and increasing the devices that depend of the wireless technology such as cell phones, PDA, and laptops. That impact of wireless technology is much broader, e.g., through sensor networks for safety applications and home automation, smart grid control, medical wear-able and embedded wireless device, and entertainment systems. For this explosion of wireless technology has raised a large demand for spectrum band. Cognitive Radio (CR) is one critical enabling technology for future communications and networking that can utilize the limited network resources in a more efficient and flexible way without interfering with primary users. It differs from traditional communication paradigms in that the radios/devices can adapt their operating parameters, such as transmission power, frequency, modulation type, etc., to the variation of the surrounding radio environment [1]. Spectrum sensing is the basic and essential mechanisms of CR to find the unused spectrum band. Cognitive Radio (CR) can detect the spectrum white space, i.e., a portion of frequency band that is not being used by the primary users, and utilize the spectrum [2].

Spectrum sensing techniques can be categorized and presented them in the following types:

- Energy Detector: it is the most common type of spectrum sensing because it is easy to implement and requires no prior knowledge about the primary signal. It still has some limitations. The first limitation it has poor performance under low SNR conditions. The second limitation of energy detection is inability to distinguish between interference from other secondary users (SUs). The last limitation is high sensing time required to achieve a give probability of detection [1] [3].

- Cyclostationary Feature Detector: There are specific features associated with the information transmission of primary user. For instance, the statistics if the transmitted signals in many communication paradigms are periodic because of the inherent periodicities such as the modulation rate, carrier frequency, etc. Such features are usually viewed as the cyclostationary features, based on which a detector can distinguish cyclostationary signals from stationary noise [1]. The feature detection technique is a method used for detecting a PU signal by exploiting the cyclostationary features of receive signal. The drawback of cyclostationary feature detection when compared with energy detection is the need for a prior knowledge of the PU signals and its implantation complexity [3].

- Matched Filtering: If SUs know information about primary user’s signal a prior, then the optimal detection method is the matched filtering [1]. The primary advantage of matched filter detection is required less time to achieve high processing gain due to coherent detection [3].

In a wireless mobile communication system, a signal can travel from transmitter to receiver over multiple reflective paths; this phenomenon is referred to as multipath propagation. The effect can cause fluctuation in the received signal’s amplitude, phase, and angle of arrival, giving rise to the terminology multipath fading. There are two types of fading effects that characterize mobile commutation: Large scale and Small scale (include
Rayleigh and Rician) fading the details of fading channels in [4].

2. RELATE WORK
In recent years, various methods for modulation classification have been developed. Popoola, J.J. and van Olst, R. developed a algorithm that is able to classify 2ASK, 4ASK, 2FSK, BFSK, QPSK, AM, DSB, SSB, FM, OFDM, 16QAM, and 64QAM [3]. Their algorithm was developed using an artificial neural network (ANN). The overall recognition success rate of combine analog and digital was found to be more than 99% even at a signal to noise ratio (SNR) as low as 0 dB.

The Richterova, M., Juracek, D. and Mazalek, A. classified the analog and digital modulation signals basis of the artificial neural network [5]. They modulation signals are AM, DSB, LSB, USB, FM, 2ASK, 2PSK, 4PSK, 2FSK, and 4FSK. The results show that the classifier has 75% probability of correctly recognizing real signals.

The algorithm by S. Gangcan, A. Jianping, Y. Jie, and Z. Ronghua utilize the complexity approach, in which a set of values of Lempel-Ziv complexity for identifying different types of modulations is developed [6]. They recognize 2FSK, 4FSK, 2PSK, and 4PSK modulation types. Their results have been presented for SNR of 10 and 20 dB only.

A. K. Nandi, and E. E. Azzouz introduce algorithms for analog and digital modulation recognition [7]. The first algorithm utilizes a decision-theoretic approach in which a set of decision criteria for identifying different types of modulations are developed. In the second algorithm the artificial neural network is used as a new approach in the modulation recognition process. They recognize the 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, and 4PSK digital modulations. Sample results have been presented for SNR of 15 and 20 dB only. In the decision-theoretic algorithm is found that the overall success rate in over 94% for a SNR of 15 dB while the overall success rate in the artificial neural network algorithm is over 96% for a SNR of 15 dB.

There are other methods that have been published deepened on the knowledge of some parameters of receive signals such as low SNR, or can be distinguished between the receive signals by only amplitude, phase, and frequency in [8] [9] [10].

The rest of this paper is organized as follows: Section 3 explain modulation signals and wireless channel. Section 4 describes the features extraction used in our system. The briefly describe ANN and discuss the simulation results in Section 5. Finally, in Section 6 the report is summed in the form of conclusion.

3. MODULATION SIGNALS AND WIRELESS CHANNEL
The digital signals are generated under Matlab/Simulink environment to be used as input to the classifier. In this paper we have following parameters: carrier frequency \( f_c = 200 \text{ kHz} \), sampling rate \( f_s = 100 \text{ MHz} \), symbol rate \( r_s = 500 \text{ kHz} \), and simulation time \( T_{(simulation)} = 2 \mu \text{ sec} \).

After generating the digital signals by simulation they were transmitted through a modeled wireless channel as multipath (Rayleigh) fading channel with no line of sight between transmitter and receiver. Its parameters are taken from the Stanford University Interim (SUI) models by IEEE 802.16 Broadband Wireless Access Working Group [11]. This document describes a set of channel models suitable for fixed wireless applications. To be specific we chose the SUI-3 channel model with omnidirectional antenna which simulates three signal paths with specific attenuation and delay [12]. The model parameters are presented in Table 1.

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<tr>
<th>Tap1</th>
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<td>-5 dB</td>
</tr>
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<td>0 µsec</td>
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The Doppler spread was considered zero. We have also corrupted the signals by Additive White Gaussian Noise (AWGN).

The digital modulation classifier being developed consists of three main blocks (see in Figure 1): (1) The pre-processing, in which the input key features are extracted from every signal segment. (2) Training and learning phase to adjust the artificial neural network structure. (3) Test phase, to evaluate the digital modulation types by simulation results.

![Figure 1](image)

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4. FEATURES EXTRACTION
The feature extraction plays a very important role directly related to the feasibility of signal recognition algorithm in CR. Those features must be sensitive to the digital modulation types and insensitive to the fading channel and SNR variation. Various feature extraction techniques exit. There are no fixed rules as to which features should be used, different researchers have used different features. The key extracted features in our paper are derived from the instantaneous phase, amplitude, and frequency.
The received real signal \( x(t) \) can be represented as signal \( z(t) \) which can be expressed as:

\[
z(t) = x(t) + jy(t)
\]

where \( y(t) \) is the Hilbert transform of \( x(t) \), and \( j \) is the imaginary unit. From the analytic signal it is easy to determine the instantaneous amplitude, phase, and frequency of the recognized signal [12].

The average value of normalized absolute centered instantaneous amplitude is given by

\[
\gamma_{\text{max}} = \text{max} |\text{DFT}(a_{\text{cn}}(i))|^2 / N_s
\]

where \( N_s \) is the number of samples per signal and \( a_{\text{cn}}(i) \) is the value of normalized centered instantaneous amplitude at time instants \( t = \frac{i}{f_s}, (i = 1, 2, ..., N_s) \) and it is defined by

\[
a_{\text{cn}}(i) = a_n(i) - 1, \quad \text{where} \quad a_n(i) = \frac{a(i)}{m_a}
\]

where \( m_a \) is the average value of instantaneous amplitude.

\[
m_a = \frac{1}{N_s} \sum_{i=1}^{N_s} a(i)
\]

The maximum value of spectral power density of normalized centered instantaneous amplitude \( \gamma_{\text{max}} \) of the receive signal is used to discriminate between frequency modulations (2FSK, and 4FSK) on one hand, amplitude and phase modulation (2ASK, 4ASK, 2PSK, 4PSK, and 16QAM) on another hand [12] [10].

The average value of normalized absolute centered instantaneous phase deviation \( m_{\text{pd}} \)

\[
m_{\text{pd}} = \frac{1}{N_s} \frac{1}{\text{max}|\varphi_{\text{nl}}(i) - \varphi_{\text{nl}}(i-1)|} \sum_{i=1}^{N_s}|\varphi_{\text{nl}}(i) - \varphi_{\text{nl}}(i-1)|
\]

where \( \varphi_{\text{nl}} \) is the centered non-liner component of the instantaneous phase.

\[
\varphi_{\text{nl}}(i) = \varphi_{\text{uw}}(i) - \frac{2 \prod f_i}{f_s}
\]

where \( \varphi_{\text{uw}} \) is the centered unwrapped phase sequence of \( \varphi(i) \) and \( 2 \prod f_i/f_s \) is linear component of instantaneous phase.

The centered non-liner component of the instantaneous phase \( \varphi_{\text{nl}} \) is used to discriminate between the 2ASK, 2PSK, 4PSK, DPSK, and 16QAM [12] [10].

5. ARTIFICIAL NEURAL NETWORK & SIMULATION RESULTS

a. Artificial Neural Network Structure

The neural network is massively parallel computing systems of an extremely large number of simple processors with many interconnections. In this paper the feed-forward network is used as Multi-Layer Perceptrons (MLP).

The structure of the MPL is a two layer with number of input neurons determine by the number of features and the number of output neurons equal to the number of modulation types to be classified. The number of neurons in hidden layer is arbitrary, depending on number of classes and training algorithm [13].

Two neurons are used at the input layer corresponding to the number of input features, ten neurons are used at the hidden layer and the network has eight neurons at the output layer corresponding to the number of target (Figure 2).

![Figure 2 The Structure of the Neural Network](image)

The generated data, consisting of input vectors and target vectors, were important into a MATLAB environment. We are partitioning the loaded data into training, validation, and testing data sets were carried out.

Seventy percent of our data was used for network training. The training was done until the mean square error (MSE) used as performance function was minimum. Fifteen percent of total data was used to validate the network was able to generalize and stop training before the network over fitting. The last fifteen percent of total data was used as a completely independent test data to test the network generalization.
b. Simulation Results
The performance of developed ANN was evaluated using 15% of total generated data as test data. The test data results are displayed in confusion matrices. The confusion matrices are very practically visualization tool for classification problems because they clearly portray the confusion between one class and each of the others. Thus, all possible permutations between inputs and possible outputs with the respective percentages are easily visualized [14].

The results are presented in Figure 3 and Figure 4 at SNR of 10 and 20 dB respectively. We have used 200 signals realization for each type of digital modulation. The results show that 8 modulations have been recognized with average success rate above 80% for signals with SNR value 10 dB and 85% for signals at 20 dB without a pre-knowledge of the signals parameters. From the results we show that the overall success rate recognition in ANN an increase as SNR value increase.

6. CONCLUSION
In this paper we present the ANN can be used for noise robust classification of digital modulations. Our contribution have been done by using multipath fading channel and distributed by AWGN to simulate more a realistic scenario.

For cognitive radio, it’s interesting to Dynamic Spectrum Access (DSA). The output of this study will provide of sensing and detecting all forms of primary users (PUs) that the types of digital signals in a CR environment. The study’s outputs give us notation the practical use an ANN in a CR technology to enable for DSA.

References

