Deep belief network for automated modulation classification in cognitive radio

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***Abstract*— In this paper, we propose low-complexity binarized deep belief network (DBN) based deep learning approach along with noise resilient spectral correlation function as a feature characterization mechanism for automated modulation classification (AMC). Through simulation results, we have shown the detection accuracy of the proposed method is above than 90% when the channel SNR ≥ 0 dB and classification accuracy remains more than 85% for all the considered modulation schemes in multi-path fading channels with SNR 0 dB. Furthermore, as shown in our simulation results, the performance of our proposed binarized DBN based method is comparable to the regular DBN for SCF pattern based AMC. We consider 4FSK, 16QAM, BPSK, QPSK and OFDM with BPSK subcarrier modulations in our simulations.**

Keywords*— *automated modulation classification; low complexity; deep learning; spectral correlation function; deep belief network

I. Introduction

Cognitive radio has attracted a lot of interest as a technique for efficiently utilizing the scarce spectrum resources [1]. Cognitive radio concept highly depends on the efficiency of the spectrum sensing [2-3]. Spectrum sensing system should be able of identify the transmissions of the primary user and other users in the same frequency band. Detecting available modulation scheme on a carrier channel is a crucial step for efficient spectrum sensing. Moreover, one of the most important requirements for implementing cognitive radio techniques is having intelligent receivers which can detect transmitted signals that change their spectral properties opportunistically. CR emerging technology also raises challenges in data security and integrity, such as jamming, interference and blocking due to ad-hoc unplanned frequency use by the other parties. To address these challenges and to enhance the Quality of Service (QoS) within a highly-congested spectrum, it is necessary to utilize modulation and coding techniques. Modulation methods, such as 4FSK, 16QAM, BPSK, QPSK, and OFDM can be used to encode data on multiple carrier frequencies. Therefore, effective modulation classification is required for CR systems to identify the modulation techniques applied for the data transmission [4].

Deep learning is an emerging area of machine learning that empower recent achievements in machine intelligent. Deep learning methods are artificial neural network (ANN) based machine learning techniques with multiple layers of ANNs. Deep learning methods are capable of learning suitable features from raw data Therefore, they are more effective in completing complex tasks [5]. Various deep learning techniques have been proposed and implemented for pattern recognition applications in areas such as, speech recognition [6-8], natural language processing (NLP) [9–10], audio and music processing [11–13], image recognition [14–16], and machine vision [17–18]. In our previous work, we proposed an automated modulation classification (AMC) method that used spectral correlation function (SCF) patterns of received signals [19]. We have used deep belief network (DBN) deep learning method to SCF pattern recognition and classification of detected modulations in received signal [19-20].

The main challenges of implementing the deep learning methods is the high computation complexity that increases the time and cost of training deep learning based classifiers. High computation complexity also results in a high power and area requirements in a possible ASIC implementation of the deep learning method. Some research work has been developed to address this issue. In [21] Courbariaux et al. introduced modified backpropagation algorithms to achieve binary weighs {-1,1}. In [22] Lin et al. proposed a binarization method for backpropagation algorithm which produces binary weighs {-1,0,1}. In [22] weights are clipped at -1 and 1 and stochastically binarized to be -1, 0, or 1 in the forward pass of the backpropagation algorithm and in the implementation of the train network. Stochastic binarization is achieved by using absolute of clipped original weights as the probability of estimated weight's absolute value becoming 1 and the sign of weight is decided by the sign of original weights.

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In this work, we extend our previous work by proposing a binarized - DBN to apply for SCF pattern classification. By using the binarized, method we represent the floating-point multiplication operations with either connection, no connection negation, or bit shifting, which is expected to reduce the power and area costs drastically in an ASIC implementation. This will be especially beneficial for systems that are very critical about power and weight costs, such as satellites. In our simulation results, we have not observed any noticeable decrease in accuracy of AMC due to the binary approximation of the DBN weights.

In the next section, we introduced the proposed system. Section III summarize the simulation results obtained and final remarks are presented in Sections IV.

II. PROPOSED SYSTEM

In Fig. 1, we illustrate the overview of the system architecture of our proposed AMC method. The proposed AMC method mainly contains two parts, SCF pattern generation and binarized DBN base pattern classification.

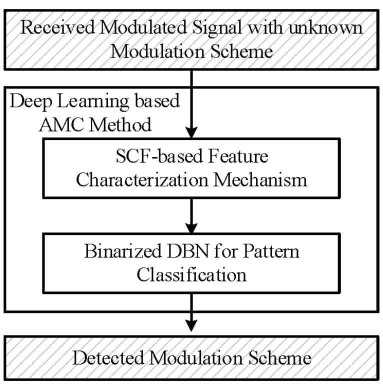

Fig. 1. Overview system architecture of the proposed AMC Method.

A. SCF-based Feature Characterization Mechanism

Cyclic Autocorrelation Function (CAF) is defined to quantize the amount of correlation between different frequency shifted versions of a given signal and represents the fundamental parameters of their second-order periodicity. CAF is calculated as follows,

$$R_x^{\alpha}[l] = \left[\lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x[n] x^*[n-l] e^{-j2\pi\alpha n} \right] e^{-j\pi\alpha l} \tag{1}$$

Where $x[.]$ is the given signal and $\alpha = m/T_0$ is the cyclic frequency when T_0 is the process period and m is an integer. Spectral correlation function (SCF) is the Fourier transform of the CAF. When f the temporal frequency of the given signal SCF is calculated as follows,

$$S_x^{\alpha}[f] = \sum_{l=-\infty}^{\infty} R_x^{\alpha}[l] e^{-j2\pi fl} \tag{2}$$

Modulated signals contain periodic statistical features corresponding to the modulation scheme. These features unique to each modulation scheme can be extracted from the SCF of the modulated signal. Being resilient to noise and other stationary impairments is an advantage of using SCF generated pattern for AMC [23-24].

B. Deep learning based classifier

The SCF pattern of the received signal is considered as a 2-D image and pre-processed before being identified by using deep learning based classifier. Furthermore, the deep belief network (DBN) based classifier uses the pre-processed SCF pattern of the received signal as the input and outputs the identified modulation scheme.

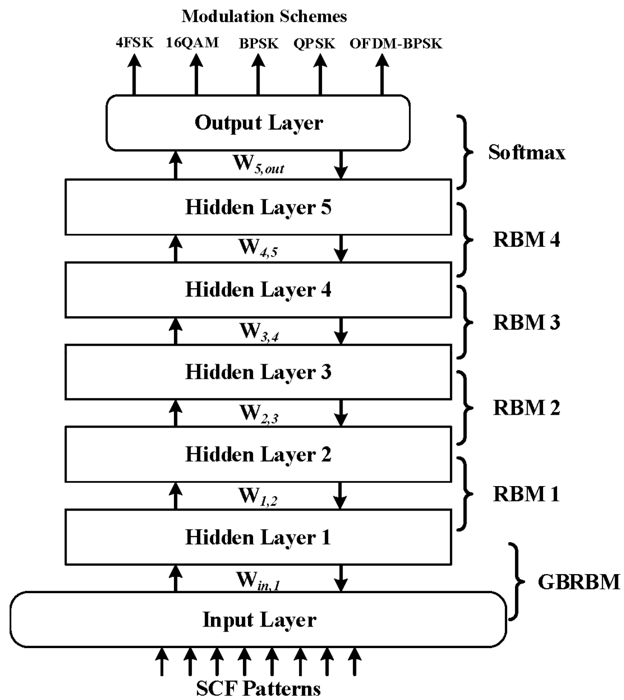

Fig. 2. The structure of the deep belief network.

Fig. 2 shows the structure of the utilized deep belief network. As illustrated in Fig.2, the DBN consists of 5 hidden layers, an input layer, and an output layer. Each hidden layer contains 32 artificial neuron units with sigmoid activation function, input layer contains 512 real-valued input units and output layer contain 5 units with softmax activation function. In this simulation, we consider five different modulation schemes, 4 frequency shift keying (4FSK), 16 quadrature amplitude modulation (16QAM), binary phase-shift keying (BPSK), quadrature phase-shift keying (QPSK), and orthogonal frequency-division multiplexing (OFDM) with BPSK subcarrier modulation, and the DBN is trained to classify these 5 modulation schemes. This can be extended with other modulation schemes as desired. DBN is trained as a stack of RBM) and a Gaussian-Bernoulli RBM (GBRBM) as indicated in Fig. 2. Details of the SCF pattern preprocessing and training procedure of the DBN is given in our previous publication [21]. In Fig. 2 $\mathbf{W}_{i,j}$ denote to the trained weigh metric connecting layers i and j.

C. Binarized DBN based classifier

As discussed in section I, the main challenge of using deep learning methods is their high computation complexity. Floating point multiplications required to be implemented are the main cause for high computation complexity. Our DBN in its original form requires a total of 20640 multiplication operation with floating point accuracy along with addition operations. To reduce the complexity of the proposed AMC system, a binarized DBN based classifier is used. Binarization of weight matrices in deep learning methods and other neural network methods is an area of ongoing research.

To binarize the DBN, we adopt the training algorithm of the [22] to backpropagation at the tuning stage of our DBN. However, since we use a GBRBM as the first RBM, $\mathbf{W}_{in,1}$ weights are normally distributed with the mean 0 and variance 0.15. Therefore, for weight matrix between the input layer and the 1st hidden layer we used the value 2^{-3} = 0.125 as the clipping value, which reduces the values of Winput,1 to -2^{-3}, 0, and 2^{-3}. Therefore, in our proposed binarized DBN, we have represented 20640 floating point multiplications to no connections, simple connections, negation, and bit-shifting operations. This result in a dramatic reduction of computation cost. The training algorithm of the binarized deep belief network is summarized in TABLE I. For simplicity, the table only illustrates the algorithm for one weight matrix **W**.

III. SIMULATION RESULTS

In this section, we briefly discuss the simulation of modulated signals and their SCF patterns. Then we compare the accuracy of our binarized DBN based method with the existing AMC methods. Then we analyze the accuracy of AMC of our binarized DBN on the simulated multipath fading channels.

A. SCF patterns of Modulation schemes

We simulate the modulated signals by encoding random data streams of 128 bits for individual modulation techniques. For all simulated signals, the carrier frequency is selected as 1 kHz and the symbol rate is chosen to be 100 Hz. The amplitudes of the signals are normalized to the range [0, 1]. Modulated signals are simulated using MATLAB/Simulink software and SCF patterns are generated using a MATLAB Communications System Toolbox [25]. 2-D projection of the 3-D SCF patterns generated for 4FSK, 16QAM, BPSK, QPSK, and OFDM-BPSK modulations are shown in Fig. 3 (a), (b), (c), (d), and (e), respectively. More detailed 3-D SCF patterns are shown in [19].

TABLE I. MODIFIED FINE-TUNING ALGORITHM FOR BINARIZING DBN

Operators and functions: **.**≥: the elementwise more than or equal comparison of two matrices. **.**×: the elementwise multiplication of two matrices. $y = sign(x)$: if $x < 0$ $y = -1$. else $y = 1$. $y = absolute(x)$: if $x < 0$ $y = -x$, else $y = x$. $\mathbf{Y} = rand(\mathbf{X})$: randomly assigns $y_{ij} \in [0,1]$ and dim(**Y**) = dim(**X**). $y = cast(x)$: if x = true $y = 1$, else $y = 0$. **W** = *backprop*(**W**,f): applies the backpropagation gradient descent algorithm to fine-tune weights **W,** where f is a batch of training data. f = *nextBatch*(**F**, batch size): returns the next batch of training data according to batch size, **F** is the training data set. $\mathbf{W_c}$ = *clipping*(**W**, L): clips the element values of weight matrix **W** to be in the range [$-L$, L] where L is a scalar.
Inputs: L – clipping level, **W** – initial weight matrix obtained from RBM unsupervised training, **F** – training data, **T** – labels corresponding to training data, N – number of training iterations,
Output: $\mathbf{W_b}$– binarized weight matrix ($\underline{w_{ij}} \in \{-1,0,1\}$)

Steps:
For epoch ≤ N
  f **=** *nextBatch*(**F**, 50)
  W = *backprop*(**W**,f)
  If (mode(epoch,100)=0)
    $\mathbf{W_c}$ **=** *clipping*(**W,***L*)
    S = *sign*(**W**)
    P = *absolute*(**W**)/L
    T = P.≥ *rand*(**P**)
    $\mathbf{W_b}$ = *cast*(**T**) .× **S**
  End
End

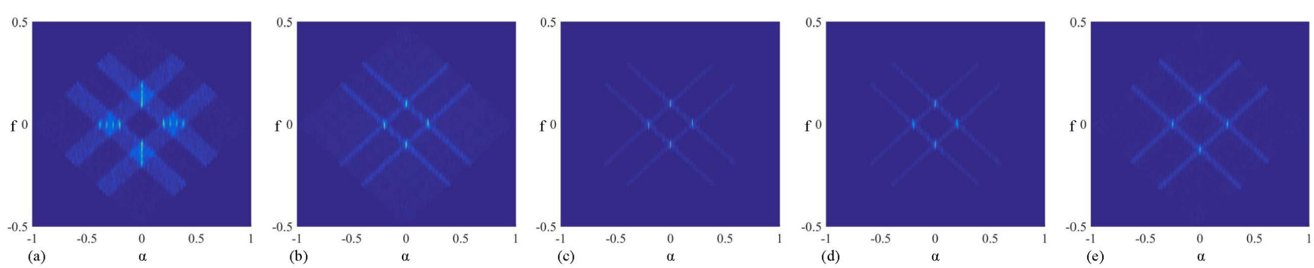

Fig. 3. 2D-SCF patterns for (a) 4FSK; (b) 16QAM; (c) BPSK; (d) QPSK; (e) OFDM-BPSK modulated signals.

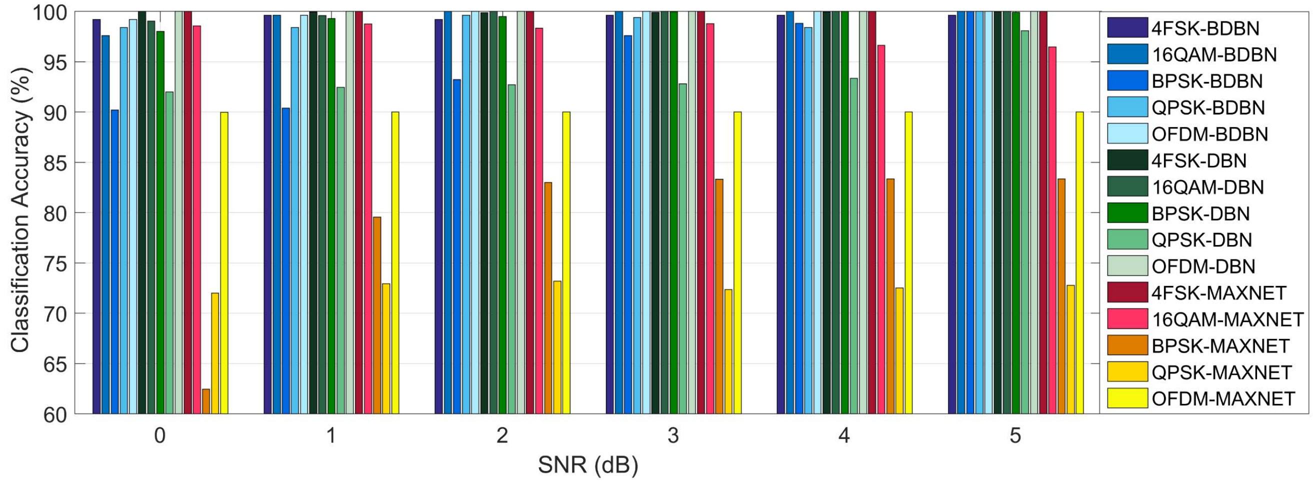

Fig. 4. Performance comparison between binarized DBN (BDBN), DBN, and MAXNET methods with different SNR values.

B. Implementation of DBN and Binarized DBN

SCF pattern sets representing all considered modulation schemes are generated using independent sequences of 2048 time samples for each modulation. Subset of points from each SCF pattern is selected to create the data set for the DBN based classifier [19]. DBN and binarized DBN are implemented used Google TensorFlow APIs [26]. 6000 data representing all considered modulation schemes are used as training data. 2000 randomly selected data are used as the verification data. Supervised fine-tuning is performed for 6000 epochs for both DBN and binarized DBN with a batch size of 50.

C. Performance evaluation for fading channel

We evaluate the effectiveness of our proposed method on a fading channel by considering SCF pattern of simulated modulated signals in environments with SNR varying from 0 dB to 5 dB. The performance of binarized DBN, regular DBN, and MAXNET neural network method discussed in [27], are compared in the Fig. 4. From Fig. 4, it is clear that the DBN methods performs better in high noise environments for modulation detection. We can also observe that binarized DBN performs equally well compared with the regular DBN.

We also simulate multipath fading channels and generate SCF patterns for different modulation schemes. Multipath fading channels are simulated according to Rayleigh fading channel model [28]. Rayleigh fading channels are widely adopted models of real-world phenomena in wireless communications. These phenomena include multipath scattering effects, time dispersion, and Doppler shifts that arise from relative motion between the transmitter and receiver. In the simulation, carrier signals received at the receiver from different paths are shifted by a random phase angle to simulate a random delay in the path and amplitude is attenuated by a random value. A random Doppler shift is also introduced to the carrier frequency with the maximum Doppler shift corresponding to the mobile speed of 65 mph (30 m/s). However, this Doppler shift is negligible considering that the radio wave travels at the speed of light. In order to affect a considerable Doppler shift the mobile speed

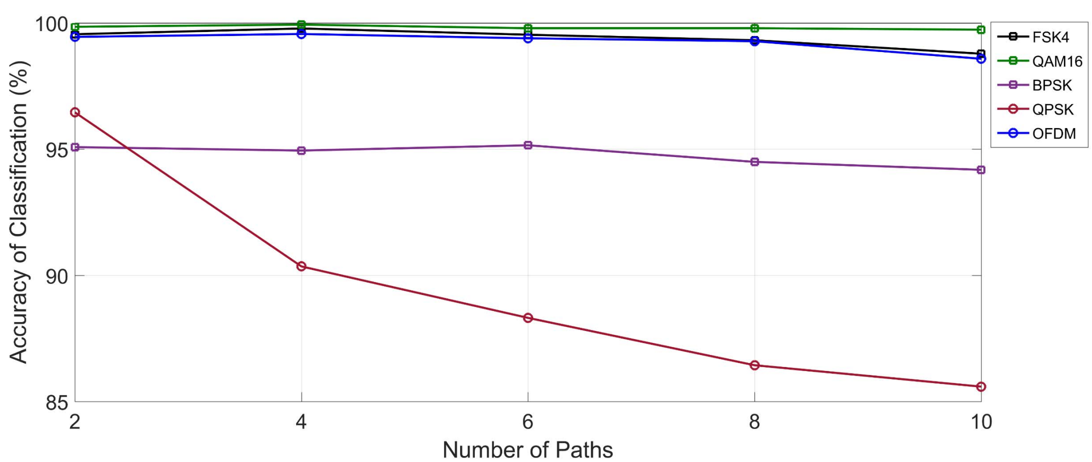

Fig. 5. The accuracy of binarized DBN in multipath fading channels.

must be comparable to speed of light which is practically not possible. Classification accuracy of the binarized DBN for different modulation scheme is shown in multipath fading channel in Fig. 5. From this figure, we can observe that accuracy remain above 90% for all modulation schemes except QPSK from 2 paths to 10 paths fading channels. QPSK classification accuracy drops below 90% when more than 2 paths fading present but remain above 85% for all considered multipath fading channels.

IV. Conclusion

In this paper, we introduce an AMC method for cognitive radio that consists of one SCF-based feature characterization mechanism and low complexity binarized DBN-based identification scheme. With the noise-resilient SCF patterns, our method can achieve high accuracy of classification even in the presence of environment noise. Furthermore, the binarized DBN technique enables us to classify modulation techniques using SCF patterns with low computation cost. Simulation results show that our proposed methods can achieve classification accuracy above 90% in fading channel with SNR > 0 dB and above 85% in multipath fading channel up to 10 paths. As future work, we plan to study the constrains of feature extraction by SCF and apply the proposed method for real-time detection of modulations in experimentally captured signals.

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