Uniting the Arts & Humanities with Science & Technology

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Deep belief network for automated modulation classification in cognitive radio

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Introduction and Motivation

- Effective modulation classification is required for spectrum sensing in Cognitive Radio (CR) systems.
- Deep Belief Network (DBN)-based classier is an effective method for Automated Modulation Classification (AMC).
- Proposed method employs DBN classier on Spectrum Correlation Function (SCF) patterns of sensed signals.
- The main challenges of implementing the deep learning methods is the high computation complexity.
- High computation complexity results in a high power and area requirements in a possible ASIC implementation.
- To overcome above, we propose a binarized - DBN to apply for SCF pattern classification.

Deep learning based AMC System

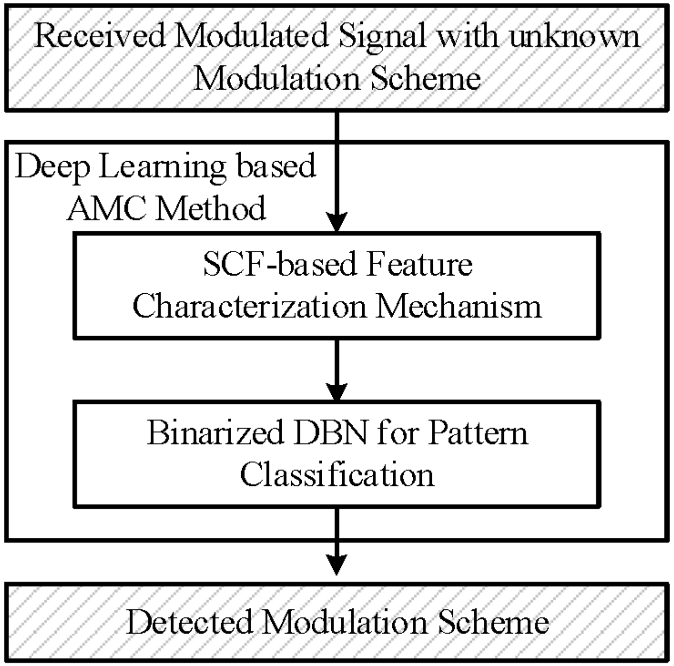

Figure: System Architecture of our proposed deep learning-based AMC method.

SCF-based Feature Characterization Mechanism

- The modulated signals are treated as cyclostationary processes that refer to the processes with periodic first-order statistics, such as mean and autocorrelation [1].
- Cyclic autocorrelation function (CAF) indicates the amount of correlation between different frequency shifted versions of a given signal and represents the fundamental parameters of their second order periodicity.
- CAF can be calculated as follows:

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

Where $x[.]$ denotes the modulated signal that is considered as cyclostationary process and α is the cyclic frequency.

SCF-based Feature Characterization Mechanism

- Spectral Correlation Function (SCF) can be obtain by calculating the Fast Fourier Transform of $R_x^\alpha[l]$.

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

Where f is the temporal frequency of the signal.

- Modulated signal received from a receiver is used as the input for our proposed SCF pattern generation mechanism which generates SCF patterns characterizing unique features of the associated modulation techniques.

Binarized-Deep Belief Network (DBN)

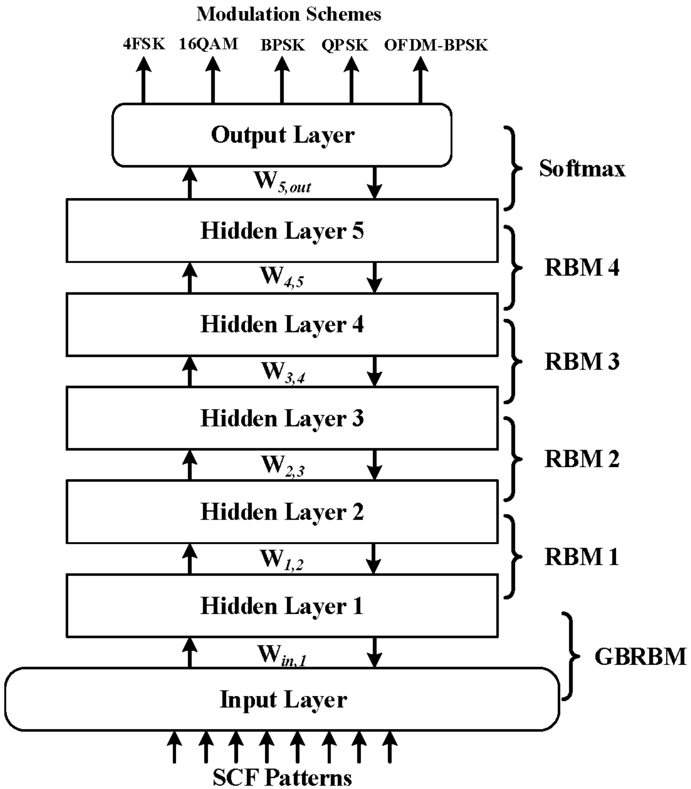

Figure: Architecture of the used binarized-DBN. Where $W_{in,1}$ contains values -2^{-3}, 0 and 2^3 and other Weight matrices contain values -1, 0, and 1.

- Binarized-DBN used in our identification scheme is formed by stacking three conventional Restricted Boltzmann Machines (RBMs) and a Gaussian-Bernoulli RBMs (GBRBMs) [2].
- Softmax layer is used as the output layer of DBN.
- DBN is trained through semi-supervised learning with SCF pattern data.
- Backpropagation fine-tuning algorithms is modified to achieve binariezed-DBN [3].

Deep Belief Network (DBN)

- Conventional RBMs consist of one visible layer and one hidden layer of binary units that do not have intra-layer connections [4].
- By training with unlabeled data, RBMs are able to learn the features embodied by the training data.
- Energy function of a conventional RBM is as follows:

$$E(\mathbf{v},\mathbf{h}) = -\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij} h_i v_j - \sum_{j=1}^{m} c_j v_j - \sum_{i=1}^{n} b_i h_i$$

Where v_j is the jth element of the vector consisting of input unit values, h_i is the ith element of the vector consisting of hidden unit values, w_{ij} is the ijth element of the weight matrix between the visible and hidden units, while b_i and c_j denote the ith and jth element of the bias vectors for the hidden layer and visible layer, respectively. Note that n and m are the number of hidden units, and number of visible units in theRBM, respectively.

Deep Belief Network (DBN)

- Based on Energy function, the activation conditional probability distributions of hidden and visible units of a RBM are shown in the followings:

$$p(h_i = 1 | \mathbf{v}) = sigm\left(b_i + \sum_{j=1}^{m} w_{ij} v_j\right),$$

$$p(v_j = 1 | \mathbf{h}) = sigm\left(c_j + \sum_{i=1}^{n} w_{ij} h_i\right).$$

Where $sigm(x) = 1/(1+e^{-x})$ is the sigmoid function.

- The update rules for weights and biases of a RBM are as follows:

$$w_{ij} = w_{ij} - \rho(< v_j h_i >_m - < v_j h_i >_d),$$
$$b_i = b_i - \rho(< h_i >_m - < h_i >_d),$$
$$c_j = c_j - \rho(< v_j >_m - < v_j >_d).$$

Where ρ denotes the learning rate, and $<.>_d$ and $<.>_m$ are the expectations computed over the data and model distribution, respectively.

Deep Belief Network (DBN)

- Based on Energy function, the activation conditional probability distributions of hidden and visible units of a RBM are shown in the followings:
- GBRBM is a variation of RBM that has a visible layer comprised of real-valued input units [5], [6].
- Energy function of the Gaussian Bernoulli RBM is defined as follows:

$$E(\mathbf{v},\mathbf{h}) = -\sum_{i}^{n}\sum_{j}^{m}\frac{v_j}{\hat{\sigma}_j^2}h_i w_{ij} - \sum_{i}^{n} b_i h_i + \sum_{j}^{m}\frac{(v_j - c_j)^2}{2\hat{\sigma}_j^2}$$

Where $\hat{\sigma}_i$ is the standard deviation of the ith element of the visible units.

- GBRBM are trained by using the following update rules:

$$w_{ij} = w_{ij} - \rho(< \frac{v_j}{\hat{\sigma}_j^2} h_i >_m - < \frac{v_j}{\hat{\sigma}_j^2} h_i >_d),$$

$$b_i = b_i - \rho(< h_i >_m - < h_i >_d),$$

$$c_j = c_j - \rho(< \frac{v_j}{\hat{\sigma}_j^2} >_m - < \frac{v_j}{\hat{\sigma}_j^2} >_d).$$

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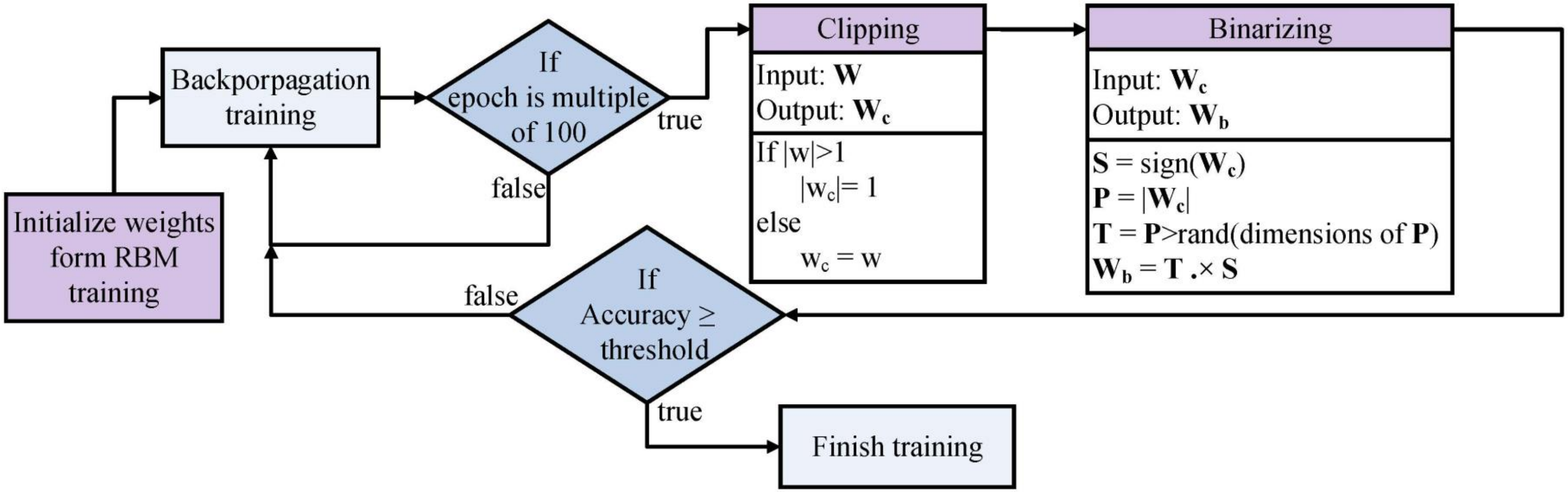
Where $\hat{\sigma}_i$ is the standard deviation of the ith element of the visible units.

- GBRBM are trained by using the following update rules:

$$\Delta z_j = e^{-z_j}\left\langle \frac{1}{2}\left(v_j - c_j\right)^2 - \sum_{i=1}^{n} w_{ij} h_i v_j \right\rangle_d - e^{-z_j}\left\langle \frac{1}{2}\left(v_j - c_j\right)^2 - \sum_{i=1}^{n} w_{ij} h_i v_j \right\rangle_m$$

Where $z_j = \log(\hat{\alpha}_j^2)$.

Modified Fine-Tuning Algorithm for Binarizing DBN



Simulation and Results

- Proposed method is evaluated for identifying signals from 4FSK, 16QAM, BPSK, QPSK, and OFDM modulation schemes.

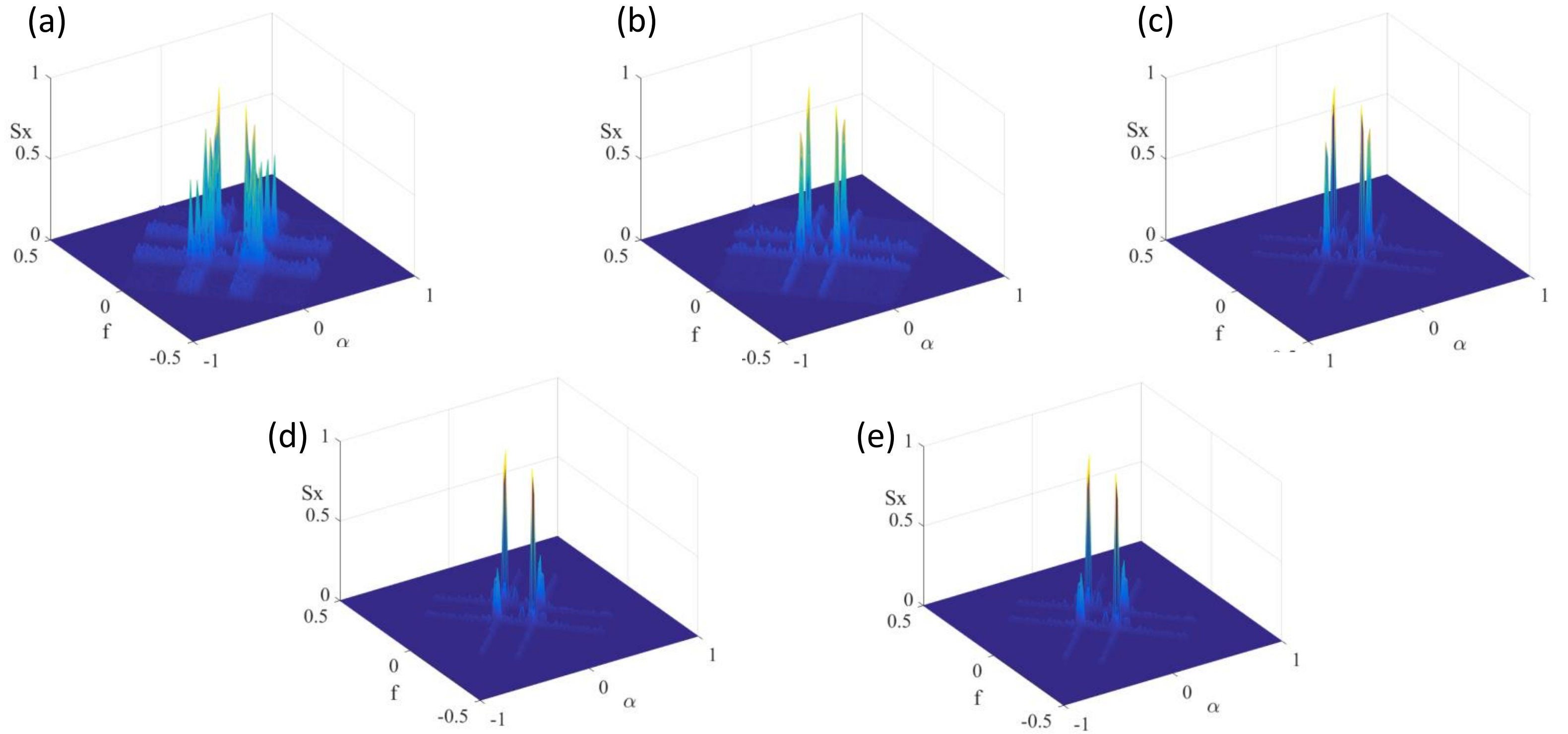


Figure: 3D-SCF patterns of (a) 4FSK, (b) 16QAM, (c) BPSK, (d) QPSK, and (e) OFDM modulation techniques.

Simulation and Results

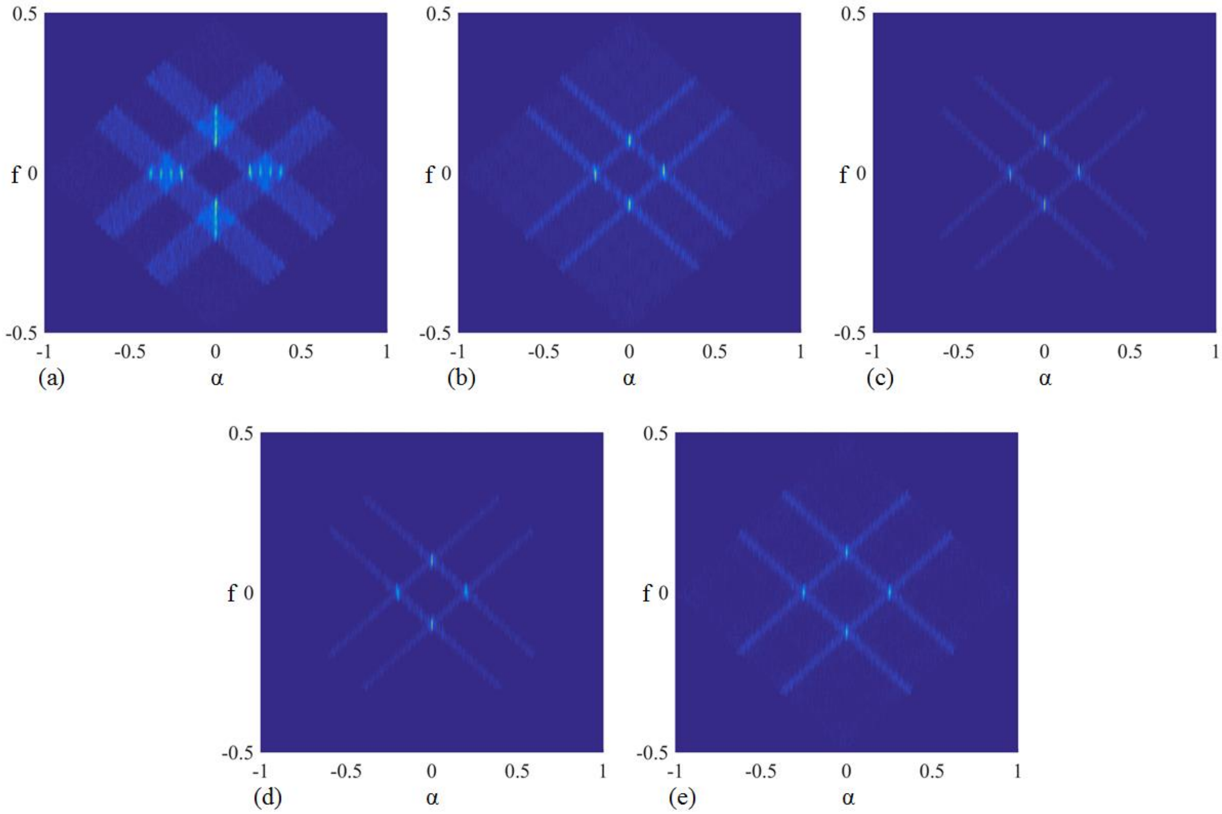


Figure: 2D-SCF patterns (XY view of 3D SCF pattern) of (a) 4FSK, (b) 16QAM, (c) BPSK, (d) QPSK, and (e) OFDM modulation techniques.

Image Preprocessing

- Gray scale images in the XY-plane of SCF patterns are first scaled to 64x64 pixels images.
- Considering the symmetric and sparse property of the patterns, a triangle with 512 pixels is selected.

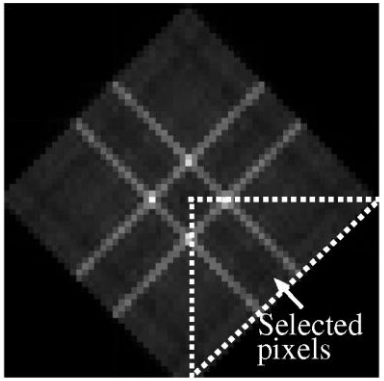


Figure: Dimension reduction for the generated SCF patterns.

- Selected pixels are represented using a vector with length of 128 that is treated as a dimensionally reduced representation of the associated SCF pattern, which is used as the feature vector for machine learning.

Results

- 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 [7].
- To further evaluate the performance we simulate multipath fading channels and generate SCF patterns for different modulation schemes. Multipath fading channels are simulated according to Rayleigh fading channel model [8].

Comparison Results

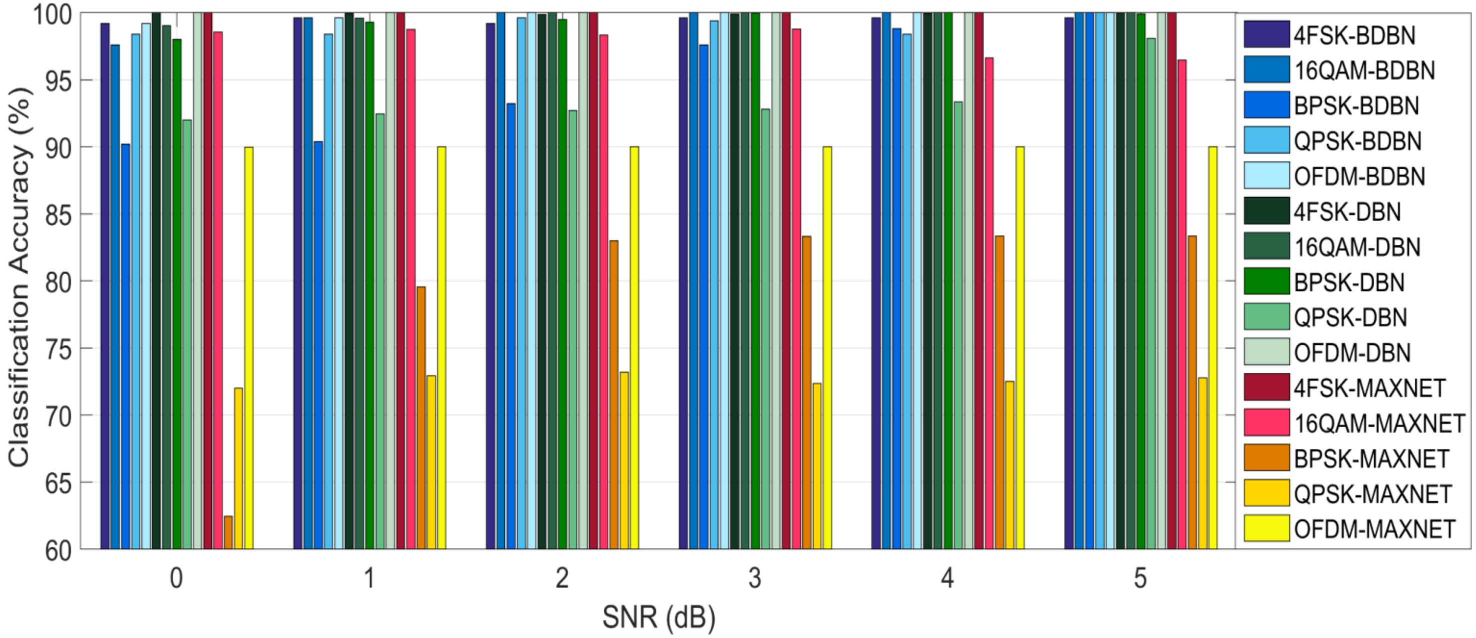


Figure: Performance comparison between binarized DBN (BDBN), DBN, and MAXNET methods with different SNR values.

- The Accuracy of binarized DBN, regular DBN, and MAXNET neural network method, are compared for classifying 4FSK, 16QAM, BPSK, QPSK and OFDM modulation techniques.
- The DBN methods performs better in high noise environments for modulation detection.
- The binarized DBN performs equally well compared with the regular DBN.

Multipath Fading

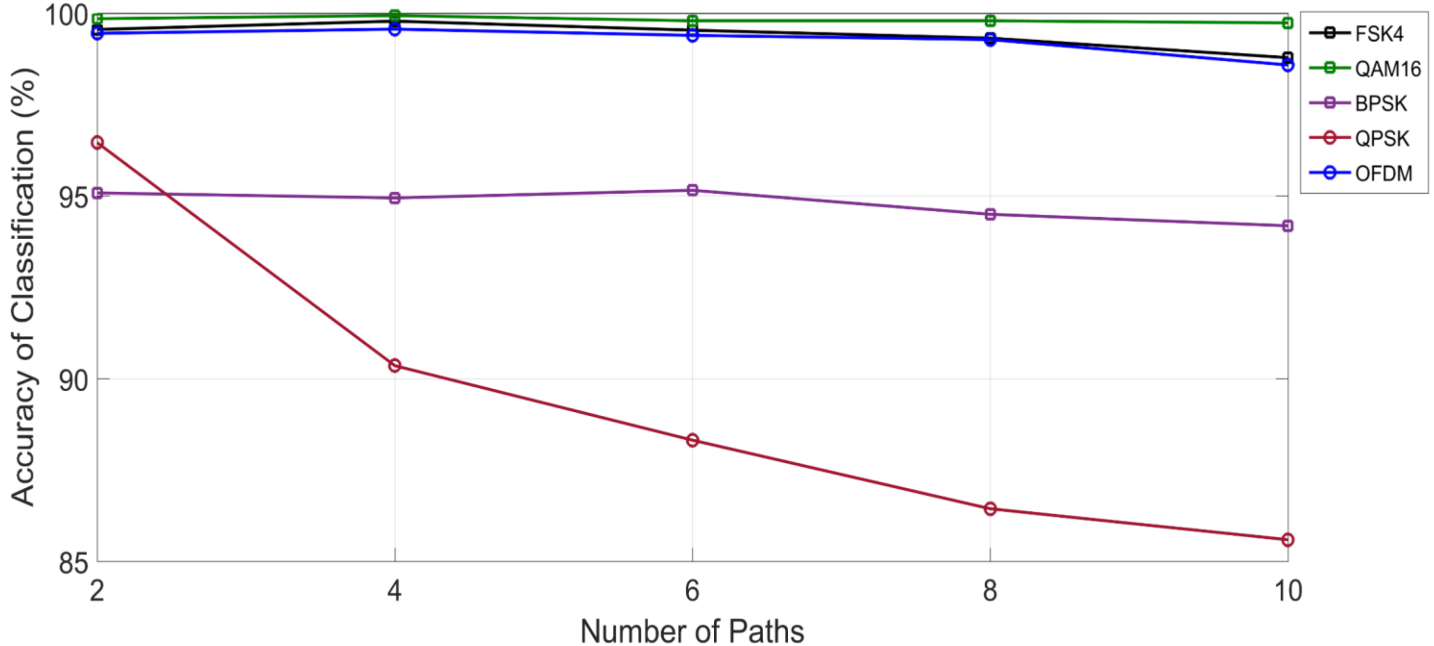


Figure: The accuracy of binarized DBN in multipath fading channels.

- 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.

Conclusion

- In this paper, we introduce an AMC method for cognitive radio.
- Our proposed framework consists of one SCF-based feature characterization mechanism and DBN-based identification scheme.
- With the noise-resilient SCF patterns, our method is able to achieve high accuracy of classification even in the presence of environment noise.
- DBN technique enables us to characterize the distinguishable features of the modulation techniques having similar associated SCF patterns.
- Simulation results show that our propose methods can achieve accuracy above 90% in classifying the modulation techniques when SNR is > −2 dB.

References

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Questions