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11/15/2017

Deep Learning-based Intelligent Method for Automatic Modulation Classification in Cognitive Radios

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Outline

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Introduction and Motivation

- Effective modulation classification is required for spectrum sensing in cognitive radio (CR) systems.
- Deep learning-based classification is an effective method for Automated modulation classification (AMC).
- Proposed method employs CNN-based classifier 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 - CNN to apply for SCF pattern classification.

Deep learning based AMC System

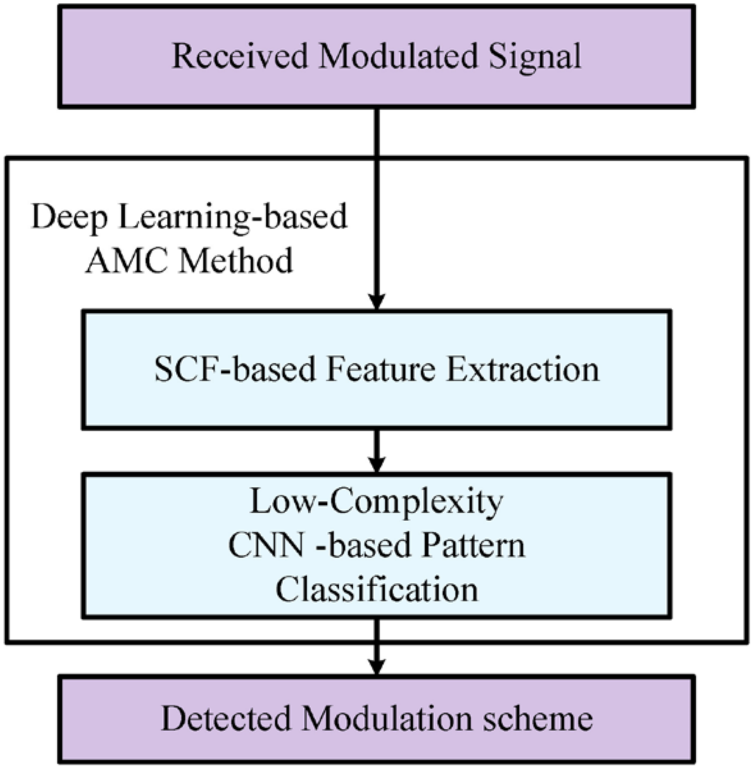

Figure 1: System Architecture of our proposed deep learning-based AMC method.

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.

SCF-based Feature Characterization Mechanism

- Modulated signals contain 2nd order periodic statistical features associated with the corresponding modulation scheme.

- 2nd order features unique to each modulation scheme can be extracted from the SCF of the modulated signal [1].

- In this work, we use SCF pattern to classify modulation schemes such as FSK, BPSK, QPSK, and OFDM. However, to identify higher order modulations, such as 16QAM and 64QAM, higher order methods need to be used [2].

- Another advantage of using the SCF patterns is the resilience to stationary impairments such as additive white Gaussian noise (AWGN) because the SCF suppresses stationary features [1].

Low-Complexity Convolutional Neural Network (CNN)

- CNN designed in our work consists of 3 convolution layers, 2 pooling layers, a fully connected layer with rectifier linear units (ReLU), and a softmax-based output layer.

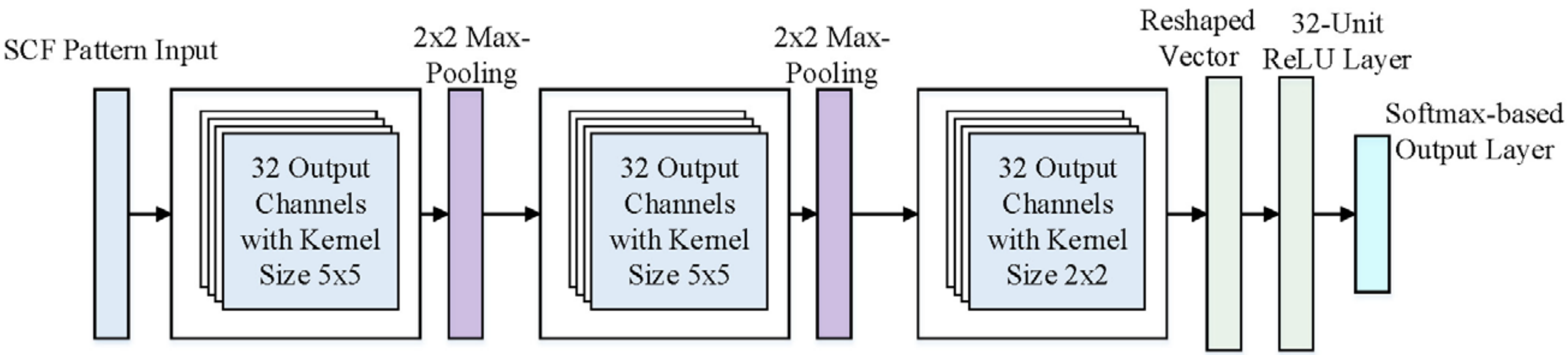

Figure 2: The Structure of CNN.

Low-Complexity Convolutional Neural Network (CNN)

- If the weights of the convolution layers and fully connected layers remain as floating-point numbers, the total number of floating point multiplication operations required to perform in a single iteration of testing is shown in the table below:

Layer	Floating point Multiplications
Convolution layer 1	$24 \times 24 \times 5 \times 5 \times 32 = 460800$
Convolution layer 2	$12 \times 12 \times 5 \times 5 \times 32 = 115200$
Convolution layer 3	$6 \times 6 \times 2 \times 2 \times 32 = 4608$
Fully connected ReLU	$1152 \times 32 = 36864$
Fully connected softmax	$32 \times 5 = 160$
The Number of Required Multiplications	617632

Low-Complexity Convolutional Neural Network (CNN)

- Floating point multiplication is computationally expensive in digital logic and the number of the total multiplications required for the CNN is very high, the deployments of the above CNN becomes a hardware-expensive task.
- By modifying training algorithm the floating-point weights of the CNN are replaced by five possible values −2p,−1, 0, 1, 2p, where p is a positive integer.
- Digital logic mapping of multiplications with low-complexity weights are shown in the table below:

Weight Value	Mapping
0	No connection
1	Connection
-1	Negation
2^p	Right shift by p bits
2^p	Right shift by p bits and negation

Low-Complexity Convolutional Neural Network (CNN)

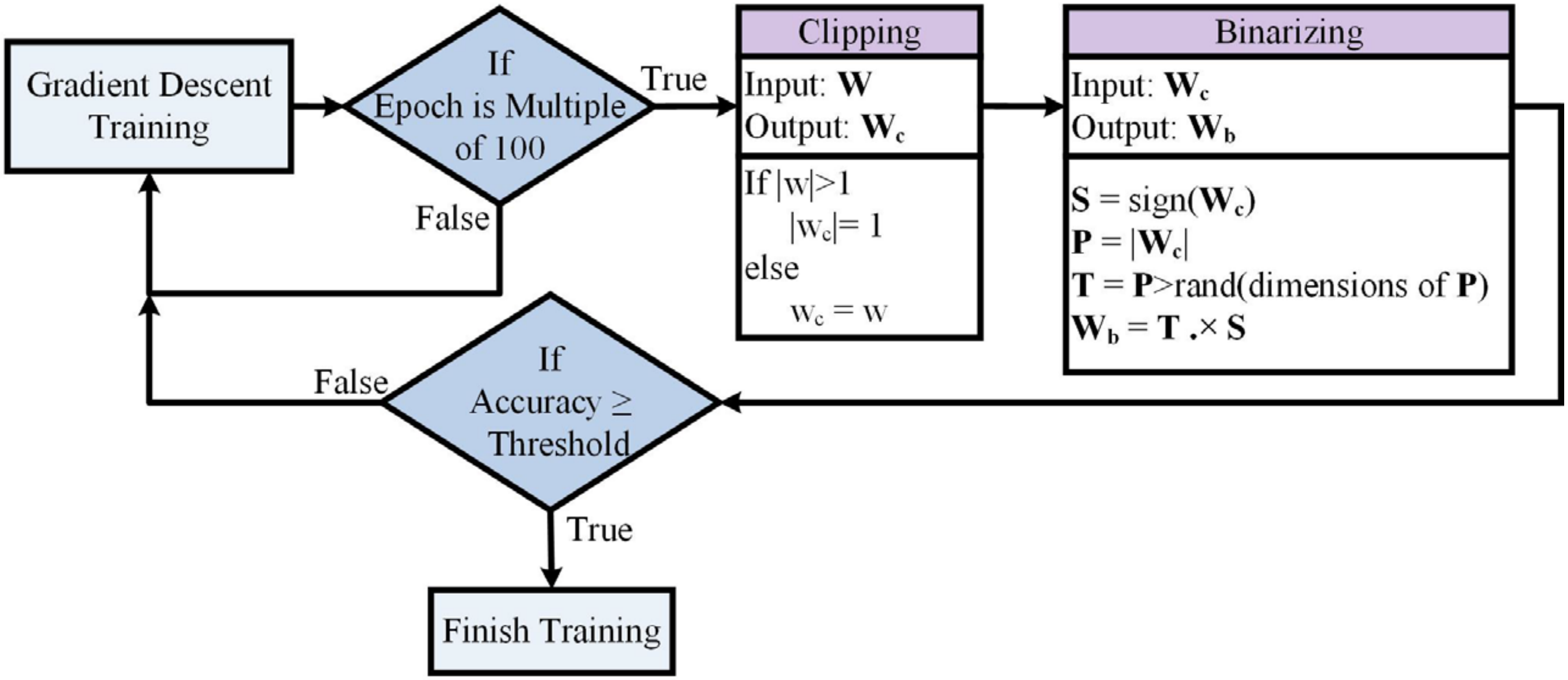

Figure 3: Modified Training Algorithm for Low-Complexity CNN.

Simulation and Results

- Proposed method is evaluated for identifying signals from BPSK, QPSK, 2-FSK, 4-FSK, and OFDM modulation schemes.
- Modulation schemes are simulated using MATLAB/Simulink software.
- 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].
- For BPSK and 2-FSK, a data stream of 256 symbols with binary symbols in random order is used. In 2-FSK, the two frequencies used are 100 Hz and 160 Hz.
- For simulation of QPSK and 4-FSK, a data stream of 256 symbols with 4 symbols in random order is used. In 4-FSK, the four frequencies used are 100 Hz, 120 Hz, 140 Hz, and 160 Hz.
- For the simulation of OFDM, 256 data random data stream is used with 4 symbols. OFDM system simulated contains 128 QPSK modulated sub-carriers.

Simulation and Results

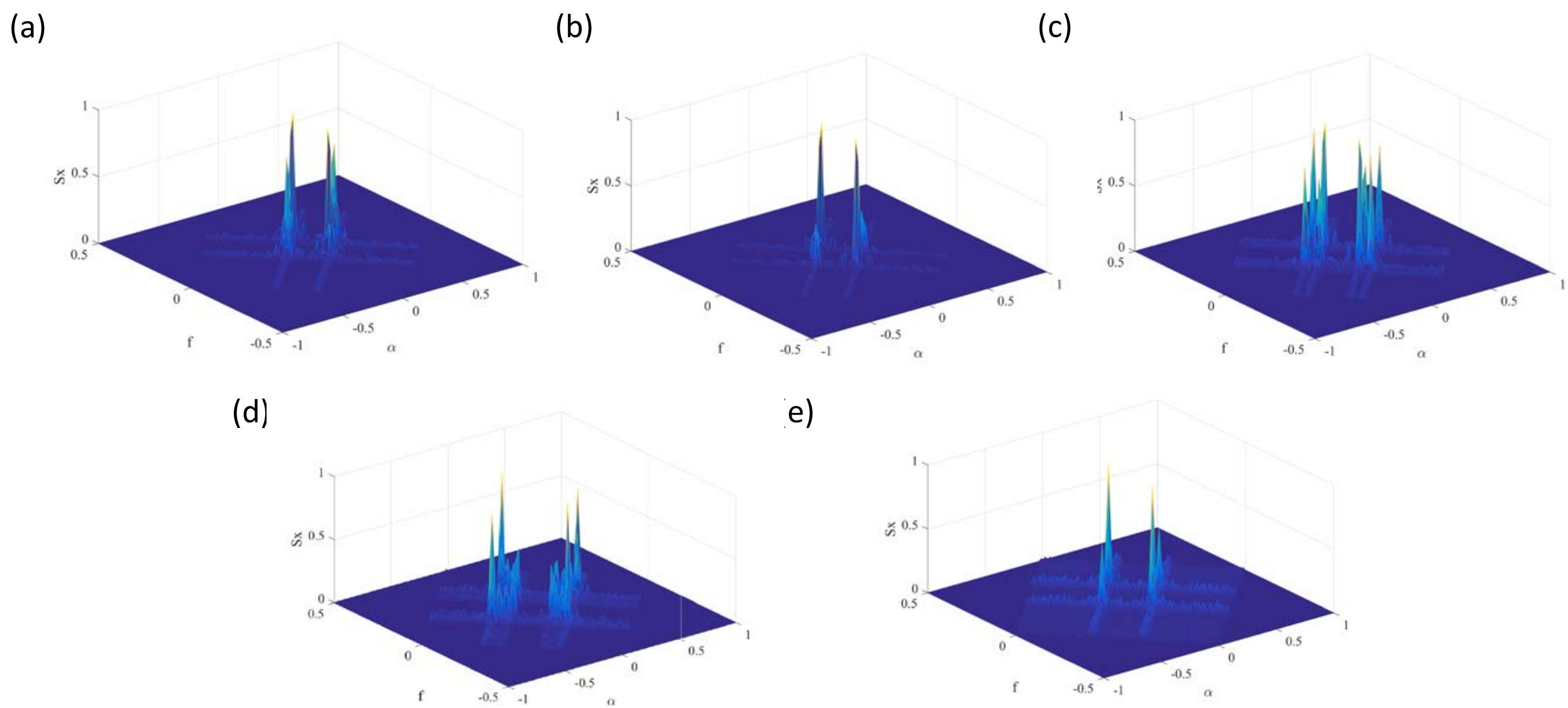

Figure 4: 3D-SCF patterns of (a) BPSK, (b) QPSK, (c) 2-FSK, (d) 4-FSK, and (e) OFDM modulation techniques.

Simulation and Results

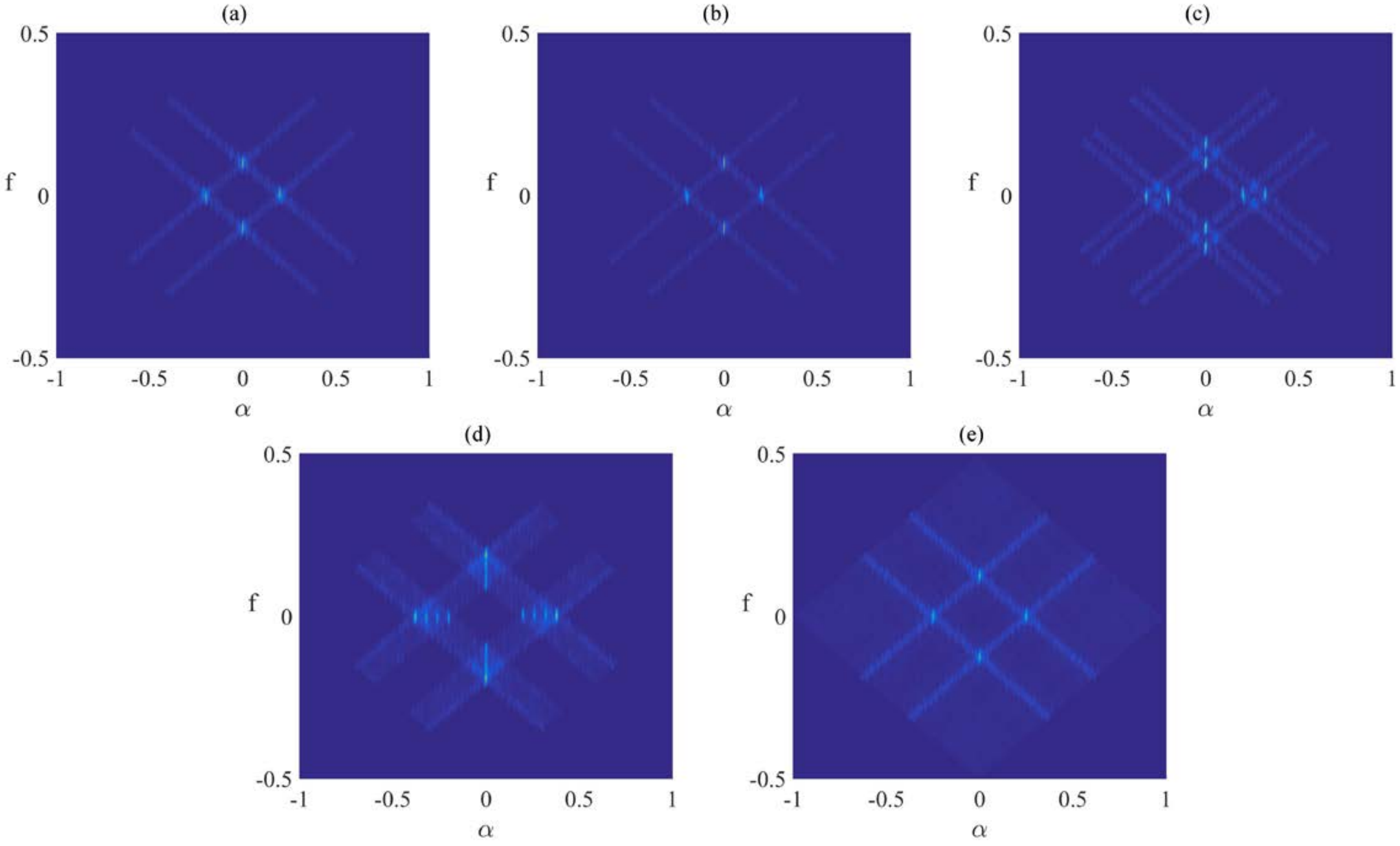

Figure 5: 2D-SCF patterns (XY view of 3D SCF pattern) of (a) BPSK, (b) QPSK, (c) 2-FSK, (d) 4-FSK, and (e) OFDM modulation techniques.

Pre-Processing and Training

- The gray-scale images of the SCF patterns are resized to be 48×48 images.
- Considering the symmetry of the patterns, a quarter of the pixels from the resized images is used as the input for the low-complexity CNN classifier. Therefore, the input size of the low-complexity CNN is 24×24.
- The low-complexity CNN is trained using data that includes 400 of 2000 patterns corresponding to each modulation scheme which contained SCF patterns generated for signals with different SNR levels.
- Another data set containing 250 patterns from each SNR for each modulation scheme is used to evaluate the performances.
- The classifiers based on low-complexity and conventional CNNs are implemented using TensorFlowAPIs [3].
- In the simulation, we set the number of iterations as 2000 and the batch size to be 20.

Results

- We evaluate the effectiveness of our proposed method on a fading channel by considering SCF patterns of simulated modulated signals in additive white Gaussian noise (AWGN) environments with SNR varying from 0 dB to 5 dB.

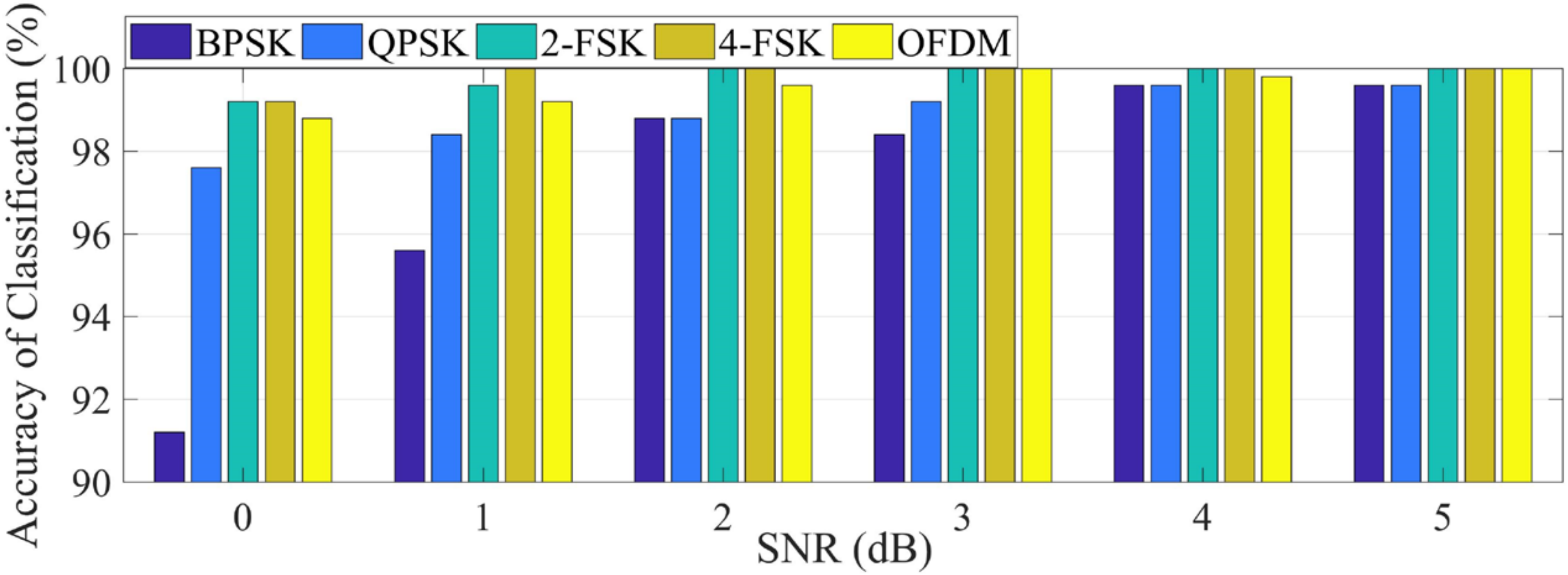

Figure 6: Accuracy of classification of modulation schemes when using low-complexity CNN as the SNR of modulated signal varies from 0 to 5 dB.

Results

- The performance of low-complexity CNN and regular CNN are compared.

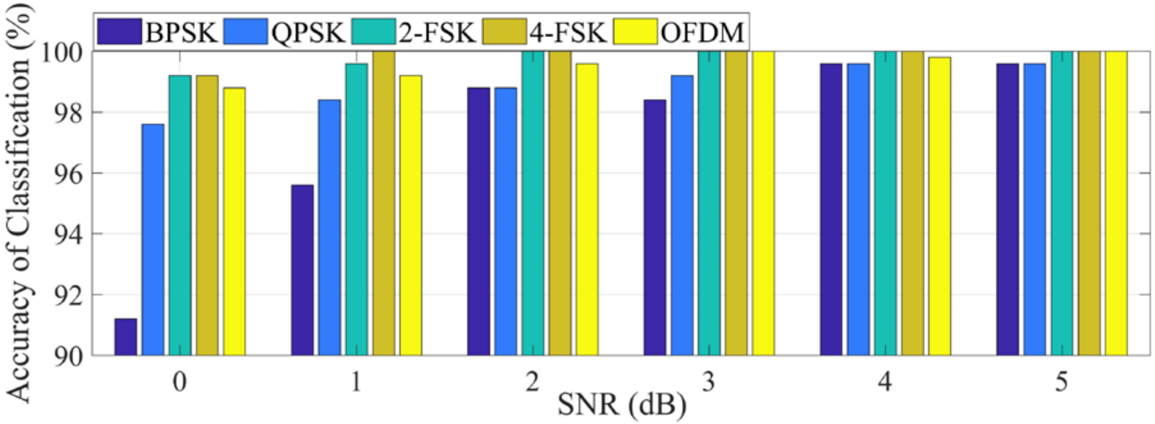

Figure 6: Accuracy when using low-complexity CNN.

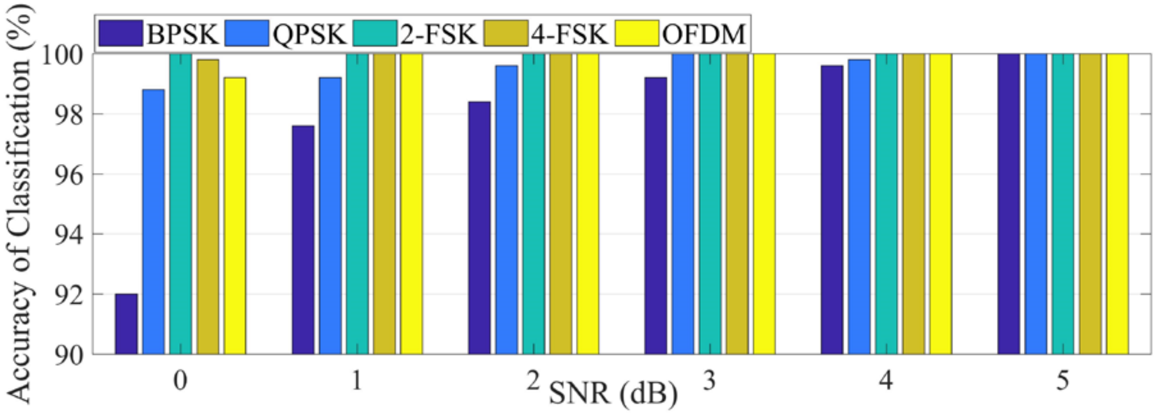

Figure 7: Accuracy when using regular CNN.

Results

- For conventional CNN, classification accuracy is above 98% for all modulation schemes except BPSK. For BPSK modulation scheme, classification accuracy observed from conventional CNN is 92%.
- For our low-complexity CNN, the classification accuracy is above 97% for all modulation schemes except BPSK. For BPSK modulation scheme, the classification accuracy observed for low-complexity CNN is 91.2%.
- Therefore, the low-complexity CNN achieves comparable accuracy in classification of modulation schemes compared with that achieved by conventional CNN.
- Furthermore, proposed CNN outperforms the conventional CNN in low computational complexity.
- Overall, our proposed CNN achieves a good tradeoff between the performance and the computational complexity.

Conclusion

- In this paper, we introduce an AMC method for cognitive radio.
- Our proposed framework consists of one SCF-based feature characterization mechanism and low-complexity CNN-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.
- CNN technique enables us to characterize the distinguishable features of the modulation techniques having similar associated SCF patterns.
- Our proposed low-complexity CNN has the advantage of containing no multipliers while a conventional CNN with the same structure requires performing 617632 floating-point multiplication operations.
- Simulation results show that our propose methods can achieve accuracy above 90% in classifying the modulation techniques when SNR is > 0 dB.

References

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2. A. Fehske, J. Gaeddert, and J. H. Reed, “A new approach to signal classification using spectral correlation and neural networks,” in *First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN 2005)*, (Baltimore, Maryland USA), pp. 144–150, Nov 2005.
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Questions

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