بسم الله الرحمن الرحيم

Performance Enhancement for Wireless Communication Systems Using Modulation and Coding Classification

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List of Publications

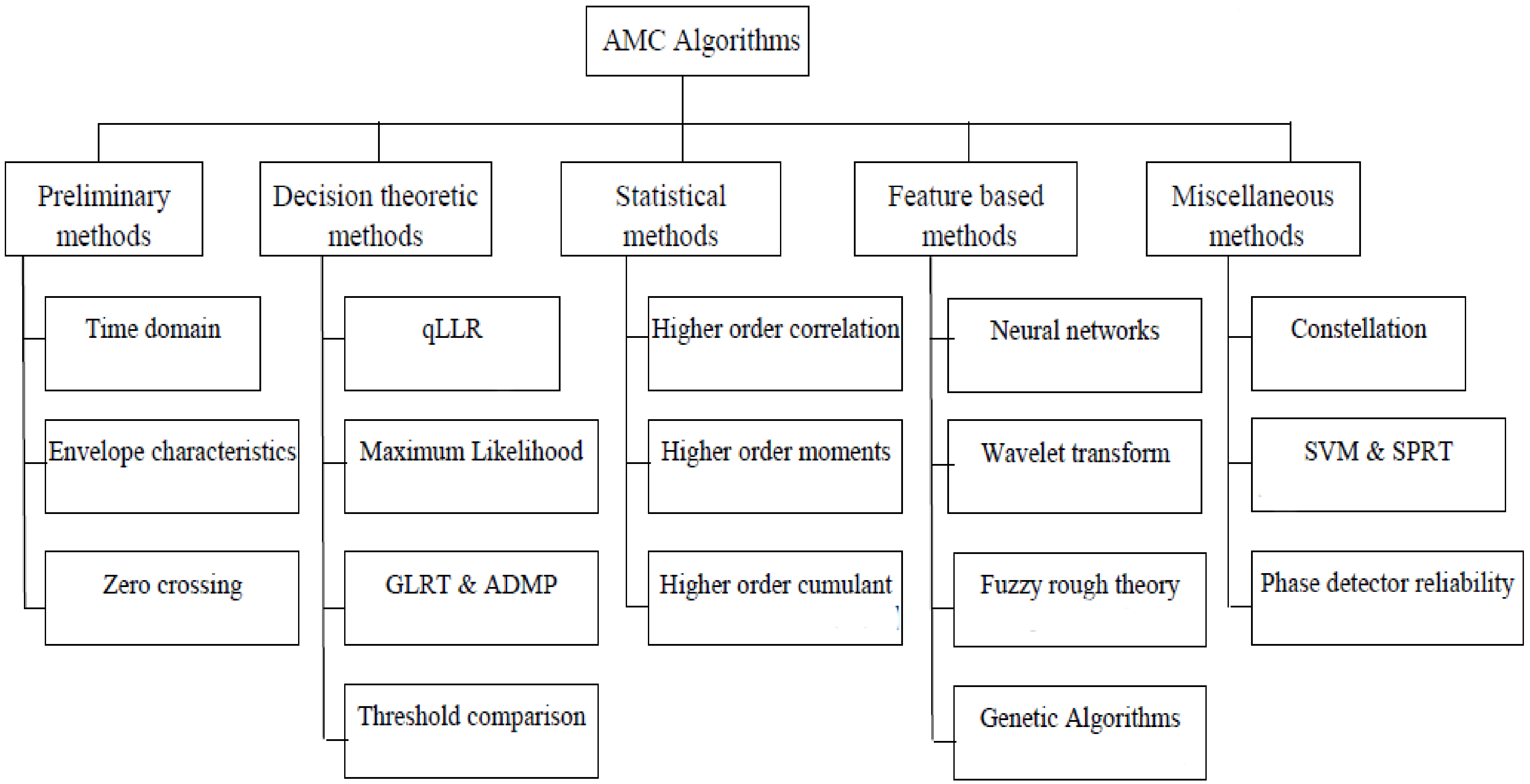
- Al-Makhlasawy RM, Hefnawy AA, Abd Elnaby MM, Abd El-Samie FE. Blind coding classification in the presence of interference in MIMO systems using ML algorithm. Int J Commun Syst. 2019; e3901.

- Al-Makhlasawy RM, Hefnawy AA, Abd Elnaby MM, Abd El-Samie FE. Modulation classification in the presence of adjacent channel interference using convolutional neural networks. Int J Commun Syst. 2019;e4295.

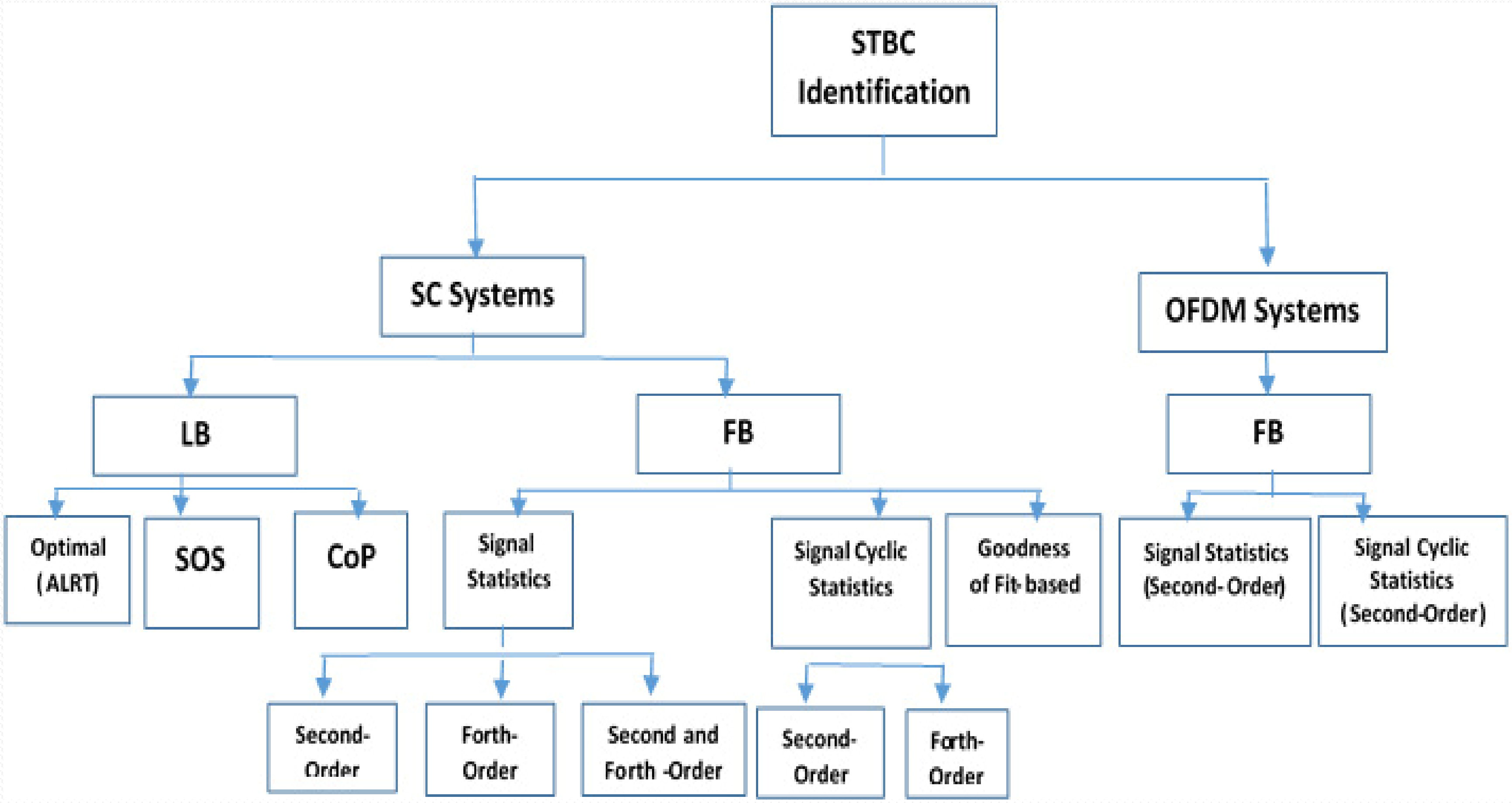
Outlines

- Introduction.
- Problem formulation and previous works.
- Coding classification.
  - Signal separation with a multi-user kurtosis (MUK) algorithm.
  - Classification with the code parameter (CP).
- Modulation classification.
  - Adjacent channel interference (ACI).
  - Convolutional Neural Network (AlexNet, VGG-16, and VGG-19).
- CNN Modulation Classification in FBMC Systems.
- Conclusions and Future Work.

Traditional Techniques Used in AMC

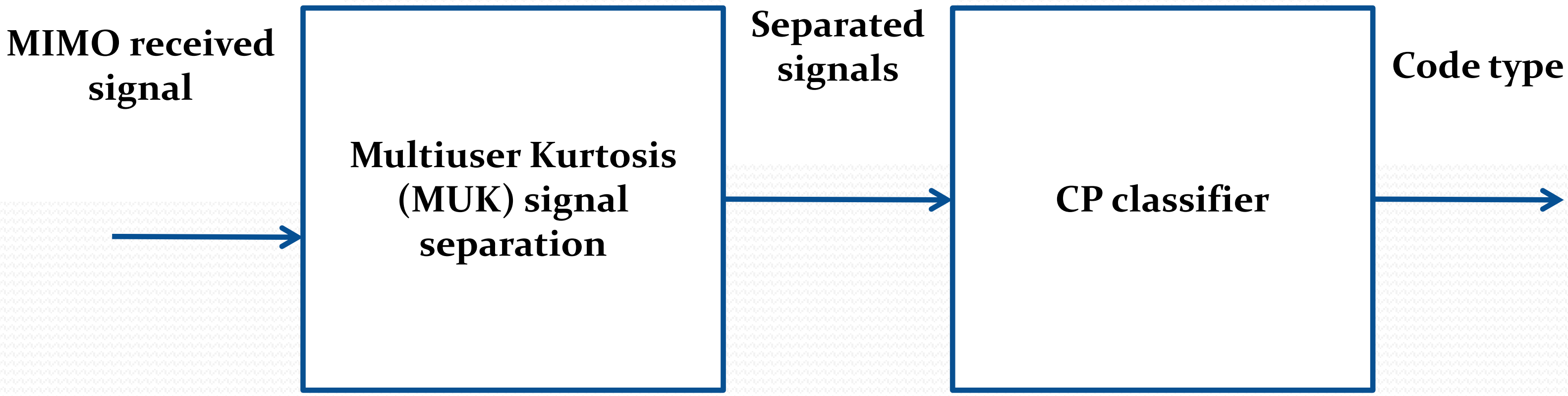


Summary of space-time block code identification algorithms



Blind Coding Classification in the Presence of Interference in MIMO Systems Using ML Algorithm

The Proposed Classifier with Signal Separation



Likelihood Ratio Tests for STBC Recognition

C is the one that maximizes the log-likelihood function of the recognized STBC

$$\hat{C} = \arg\max_{c\in\theta} \log(\Lambda[\mathbf{Y}|C, X])$$

where log $(\Lambda[\mathbf{Y}|\boldsymbol{C},\boldsymbol{X}])$ is defined as the log-likelihood function under **Y** condition

$$\log(\Lambda[\mathbf{Y}|C, X]) = \sum_{v=1}^{N_b} \log(\Lambda[\tilde{\mathbf{y}}_v|C, X])$$

where $N_b = (N/l)$ is the total number of received blocks.

Code Classification

- Identification of the code parameters n_t, n, and l blindly is enough to recognize numerous STBCs.
- If we detect the number of transmitter antennas n_t, we can recognize the AL code and OSTBC3.
- If we detect the code length, the SM and the AL code can be distinguished.
- We can recognize the code if we detect the number of symbols n without a priori knowledge of the number of antennas at the transmitter side for two codes with the same code length.

Code Classification

The covariance matrix can be formed as follows:

$$\Sigma_{n,l} = \sum_{k=1}^{2n} (\lambda_k - \sigma^2)\mathbf{v}_k \mathbf{v}_k^T + 2I_{2n_r l}$$

where $\lambda_1 \geq \cdots \geq \lambda_{2n}$ and $\mathbf{v}_1 \ldots, \mathbf{v}_{2n}$ are the eigenvalues and the eigenvectors.

Code Classification

If we ignore the terms that do not depend on the CPs, the equations become as follows:

$$\mathcal{L}(n,l) = n(4n_r l - 2n + 1) - N_b/2 \sum_{k=1}^{2n} \log(\rho_k) - N_b(n_r l - n)\log\left(\frac{1}{2(n_r l - n)}\right)\sum_{k=2n+1}^{2n_r l}\rho_k,$$

where l is the block length and n is the number of encoded symbols per block of the STBC $\mathcal{C}$. Finally, the parameters that maximize the function $\mathcal{L}(n,l)$ are the CPs l and n.

Proposed Scenario for Blind Signal Recovery

- We consider a transmitted signal through a linear MIMO channel in the presence of Inter-User Interference (IUI).

- Inter-User Interference (IUI) causes damage of the received signals.

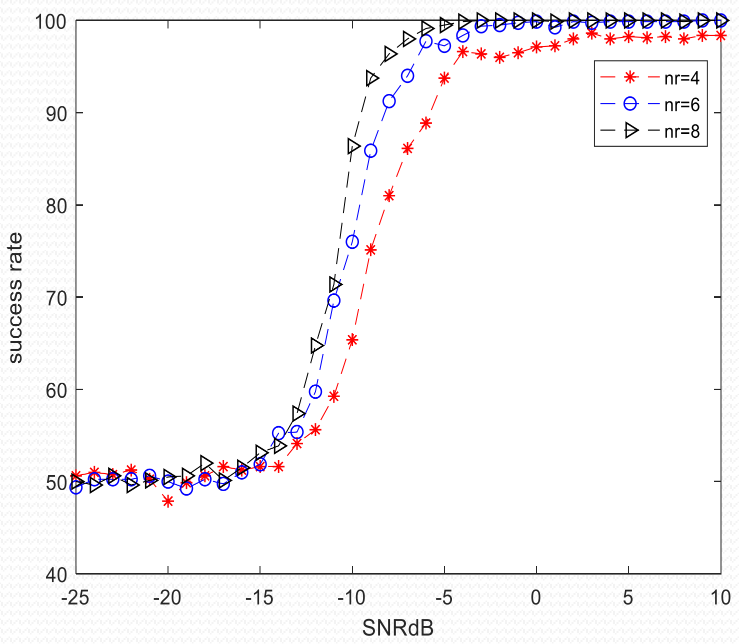
- The essence of the blind signal separation (BSS) problem is to recover the source signal from a group of sensor observations that are mixtures of the sources.

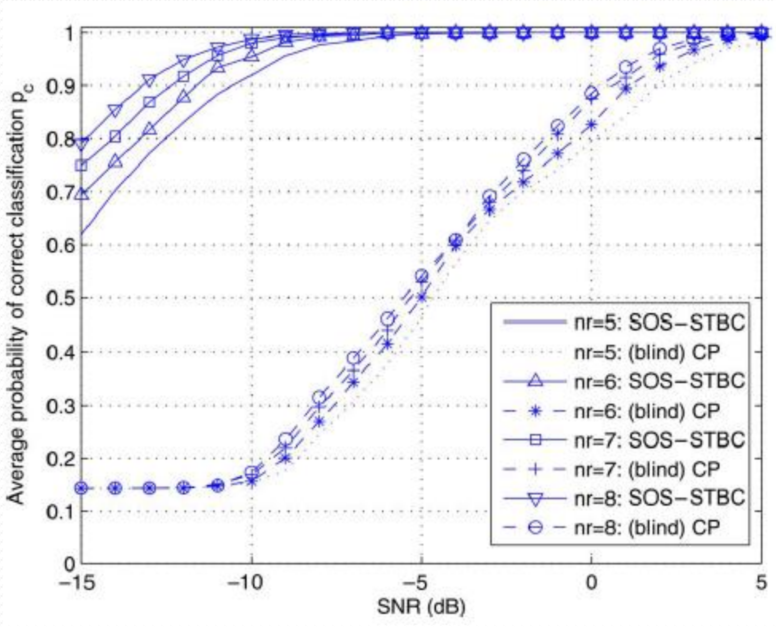
Results and Discussion

- We consider two kinds of coding, SM and AL codes, for code classification with four types of modulation, BPSK, QPSK, 8PSK, and 16QAM.
- For each modulation type with the two types of codes, we generate 1000 realizations for each using Monte Carlo simulation.
- Our proposed system does not depend on any knowledge of the received signal or any knowledge of the channel.

Influence of the Number of Received Symbols *N*

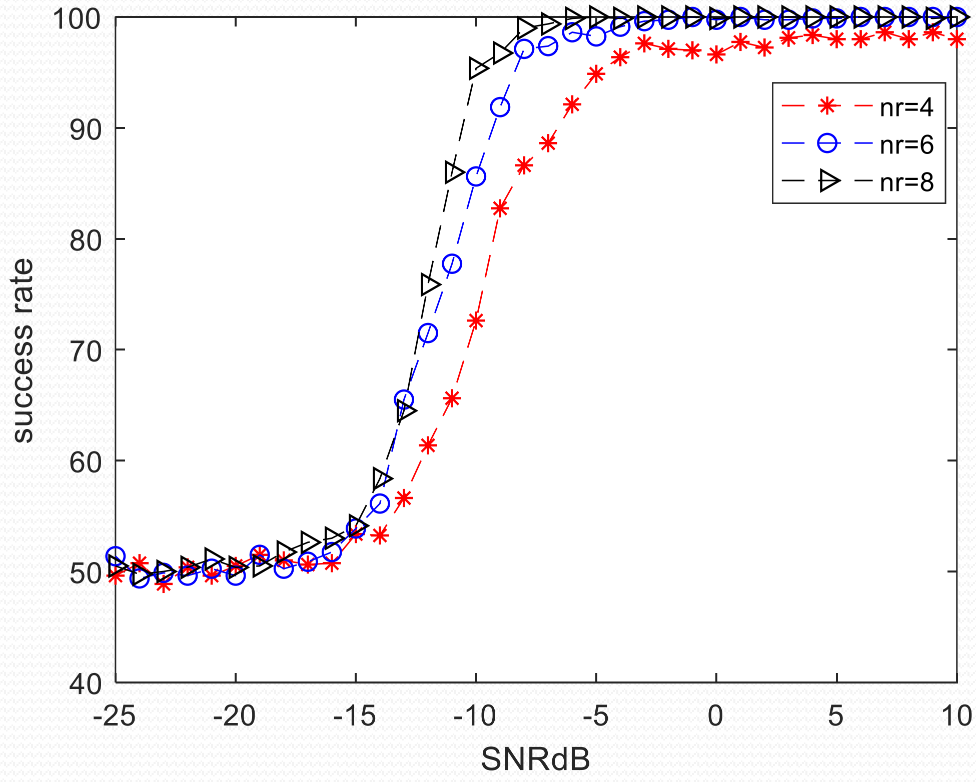
- Success rate at $N = 500$





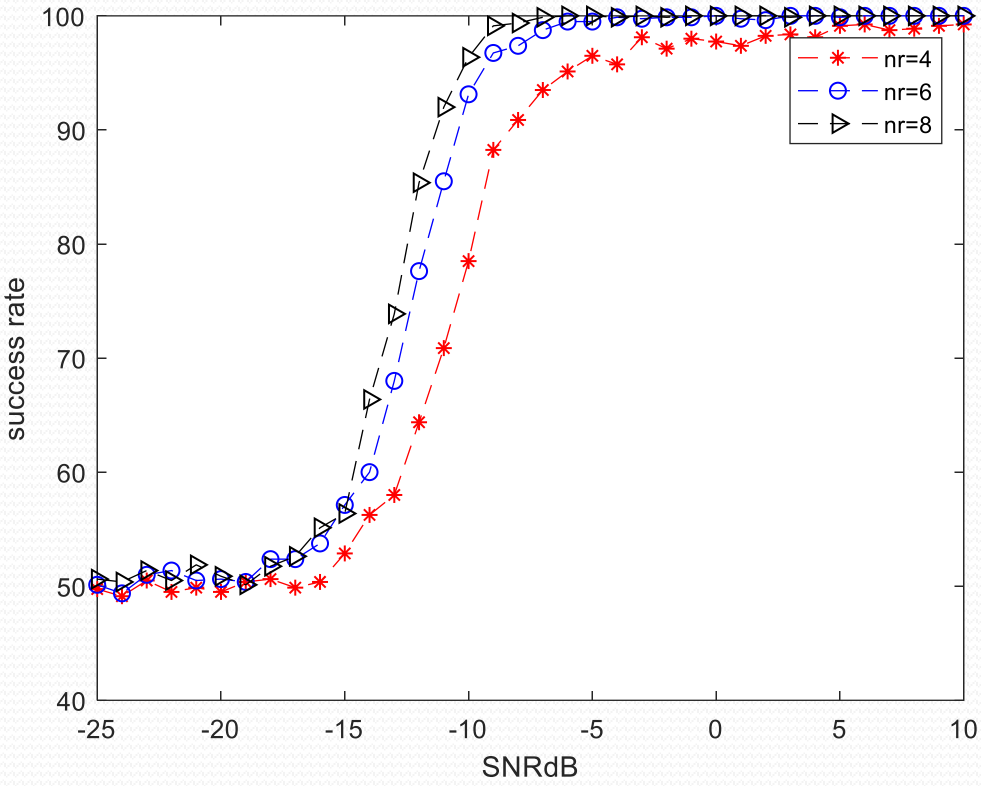
Influence of the Number of Received Symbols *N*

- Success rate at $N = 750$



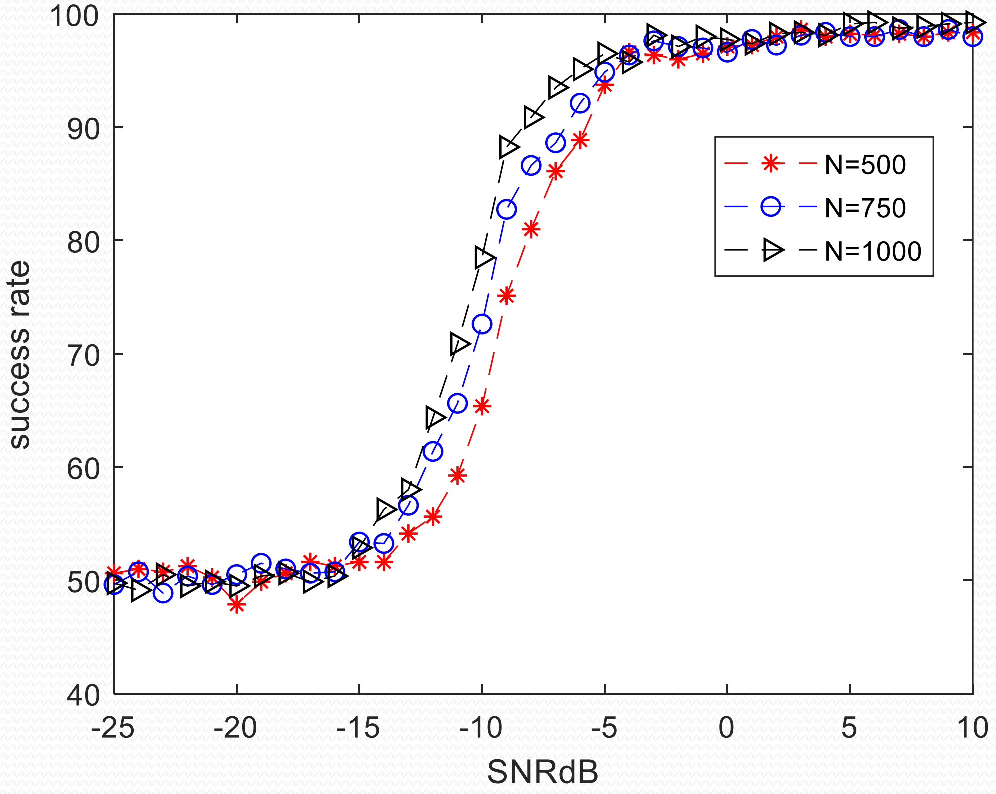
Influence of the Number of Received Symbols *N*

- Success rate at $N = 1000$



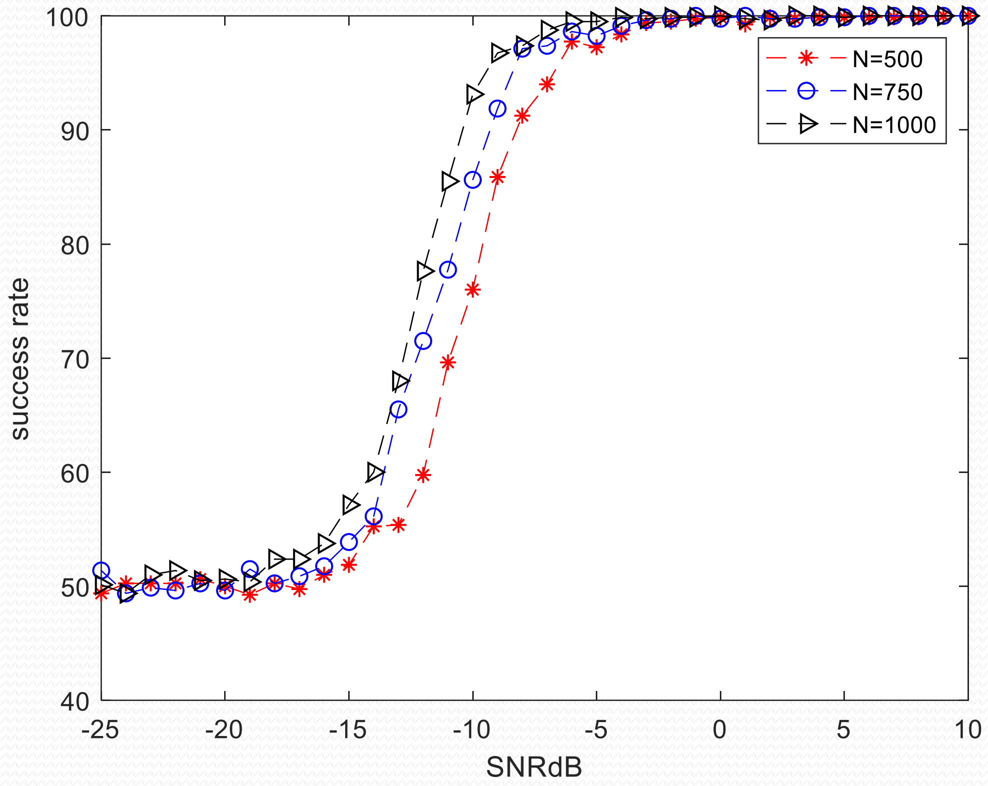
Influence of the Number of Receive Antennas n_r

- Success rate at $n_r = 4$



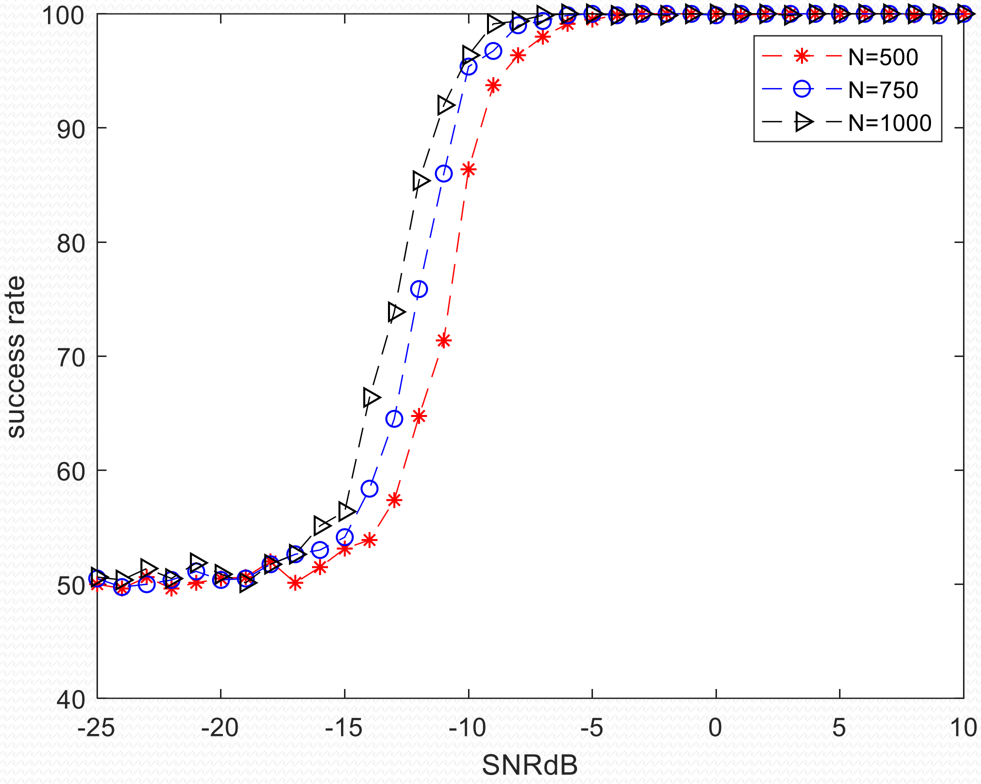
Influence of the Number of Receive Antennas n_r

- Success rate at $n_r = 6$



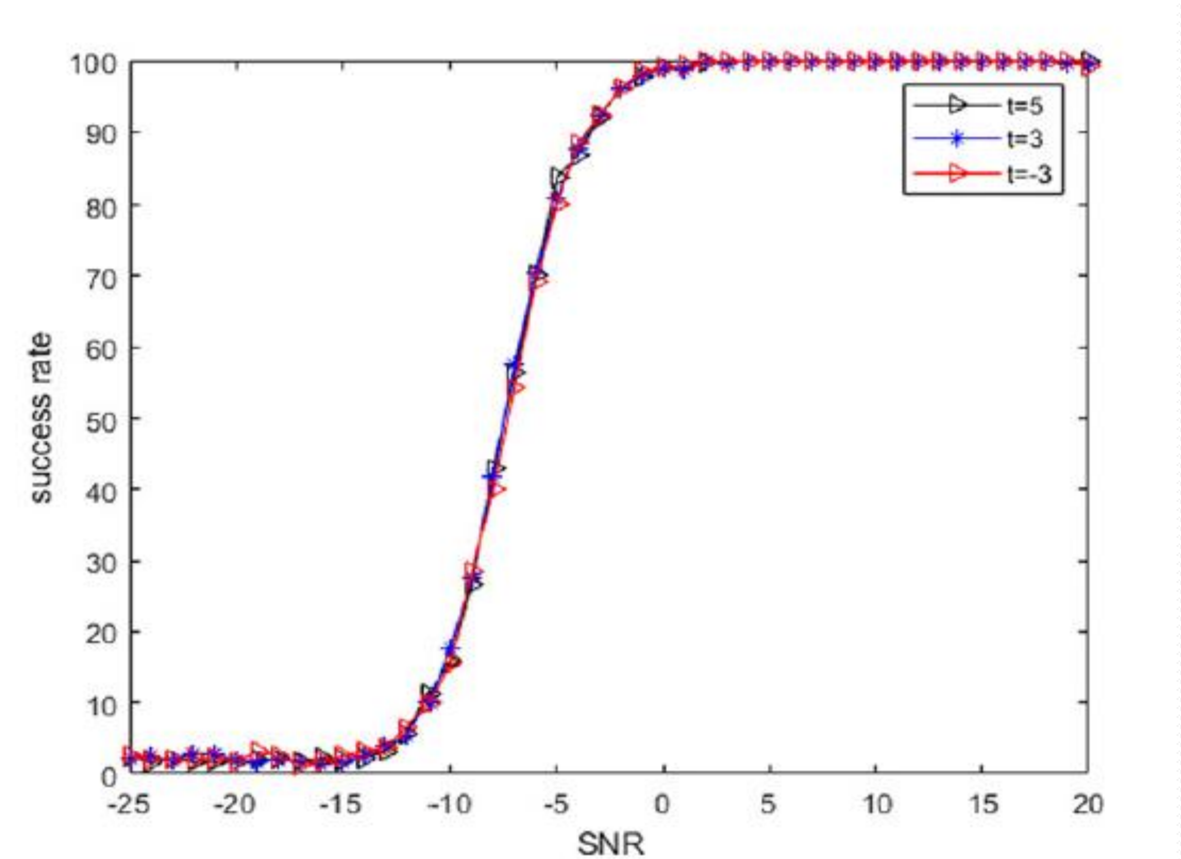
Influence of the Number of Receive Antennas n_r

- Success rate at $n_r = 8$



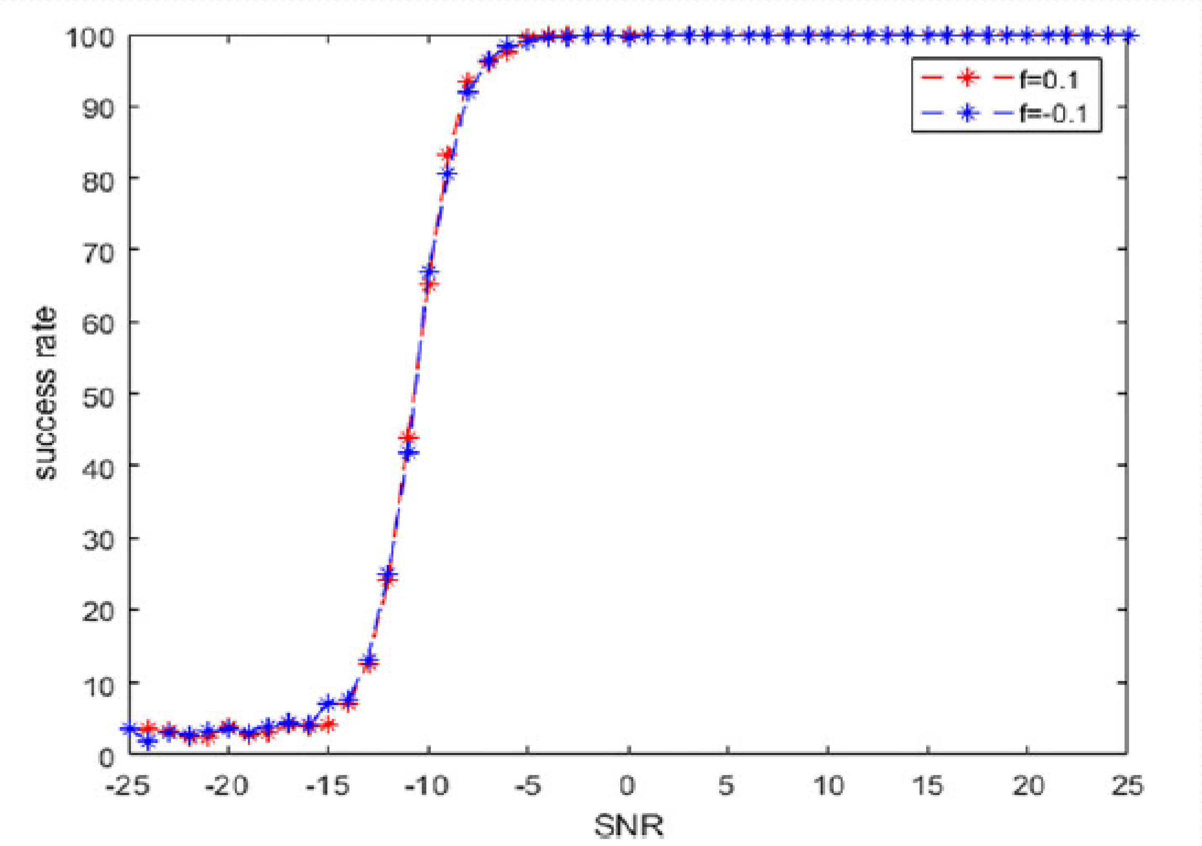
Influence of the Frequency Offset and Time Offset

- Success rate when time offset = 5, 3, −3



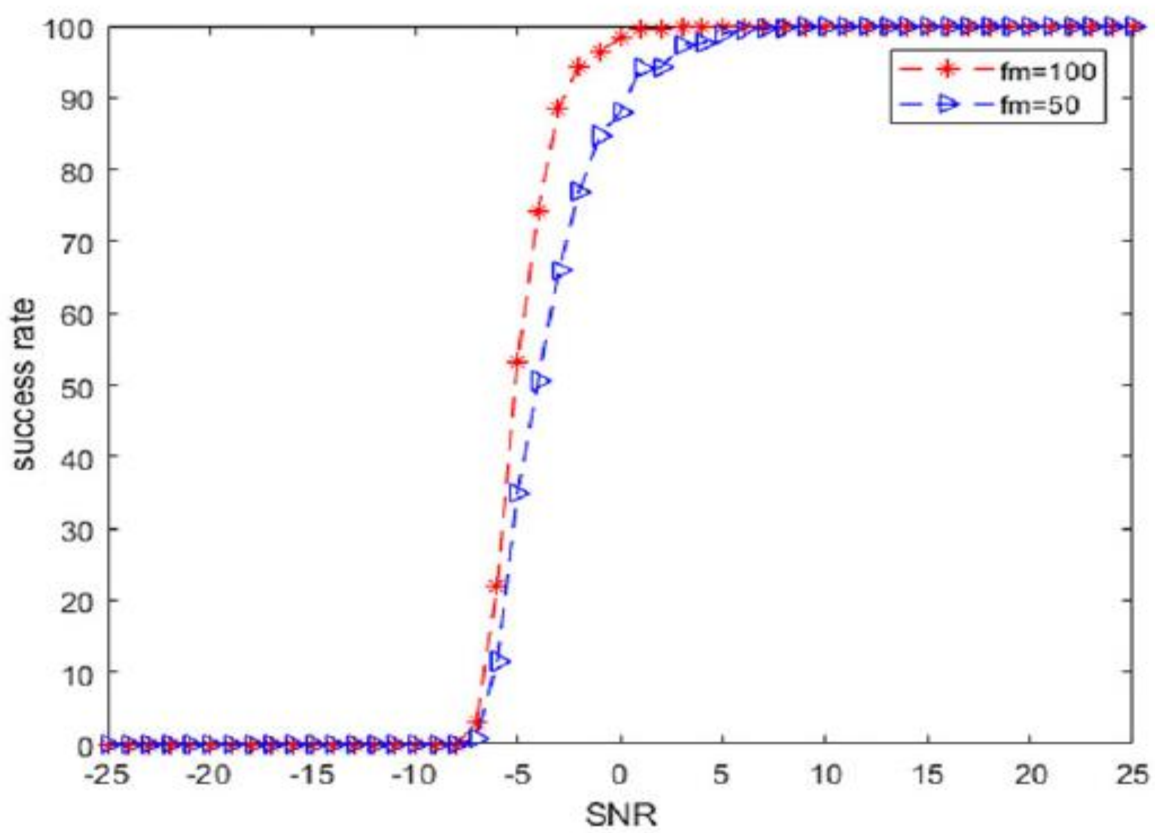
Influence of the Frequency Offset and Time Offset

- Success rate when frequency offset = 0.01, −0.01



Influence of the Doppler Frequency

- Success rate, when the Doppler frequency = 100, 50 Hz



Modulation Classification in the Presence of Adjacent Channel Interference Using Convolutional Neural Networks

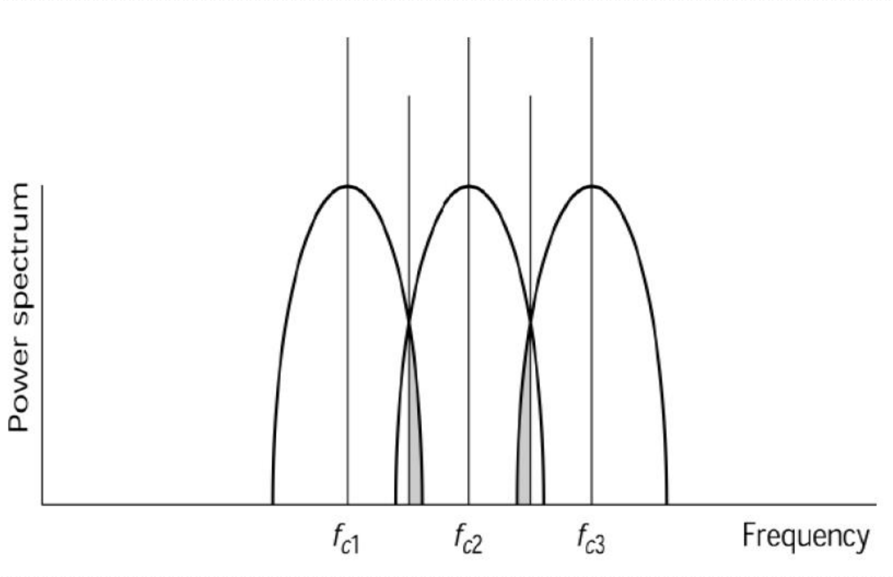
Deep Learning

- Represents a successful operation in several application fields.
- Depends on a large amount of data.
- Has an advantage that does not need manual feature extraction.
- Reduces the computational complexity in modulation classification.
- In the traditional modulation classification methods, which can be inaccurate, we require prior knowledge of the transmitted signal and channel parameters estimation.

Problem Formulation

- **Adjacent Channel Interference**

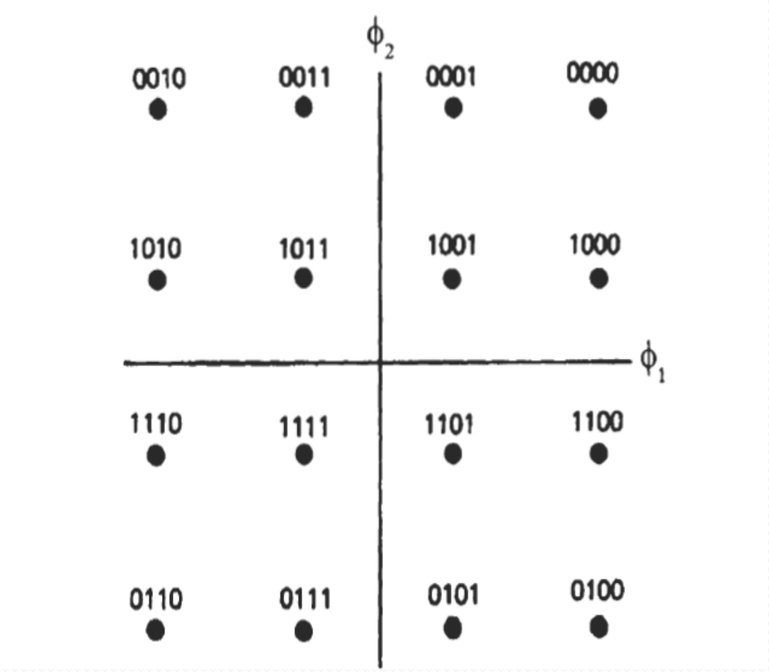
The undesirable signals from neighboring frequency channels which inject energy into the channel of.

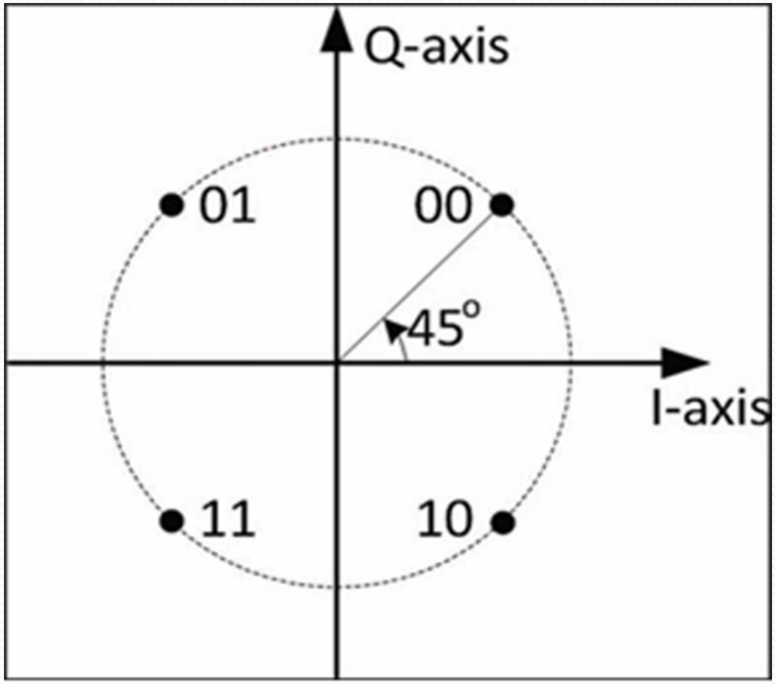


Model Description

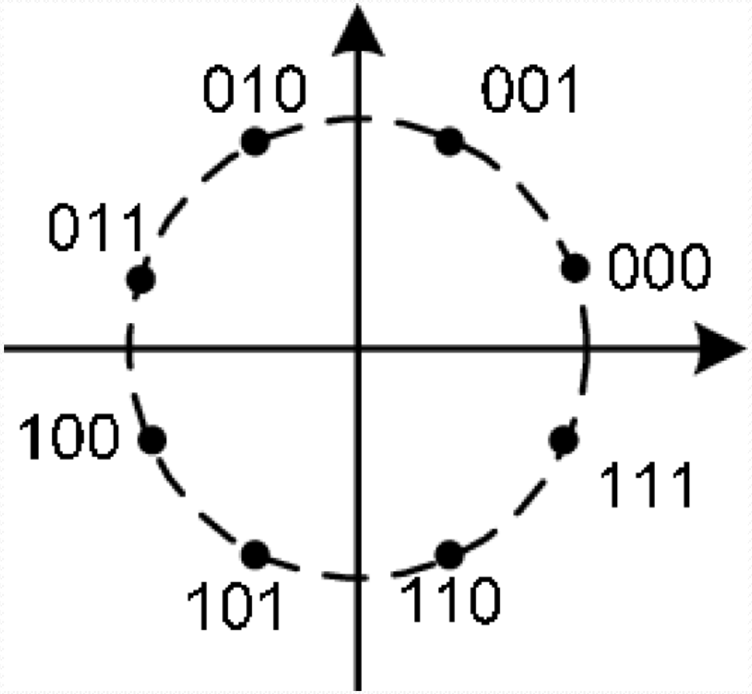
- **Digital Signal Modulation Techniques**

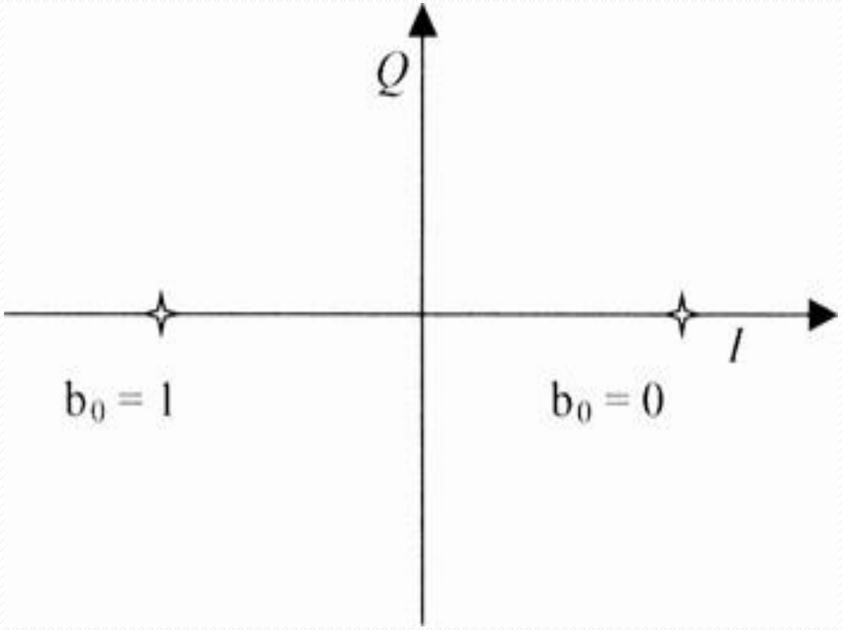
We use the Quadrature Amplitude Modulation (QAM) and Phase-Shift Keying (PSK) digital modulation techniques.



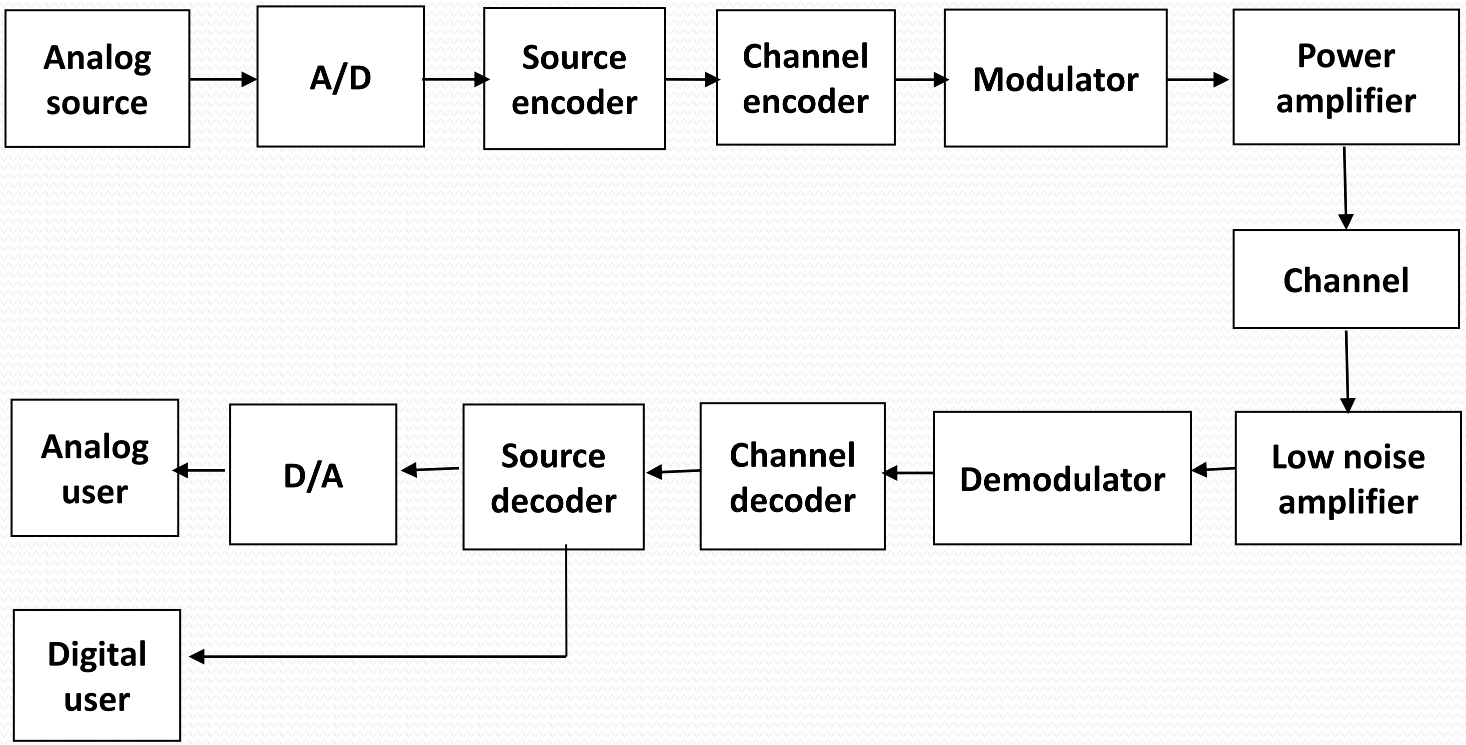


Model Description





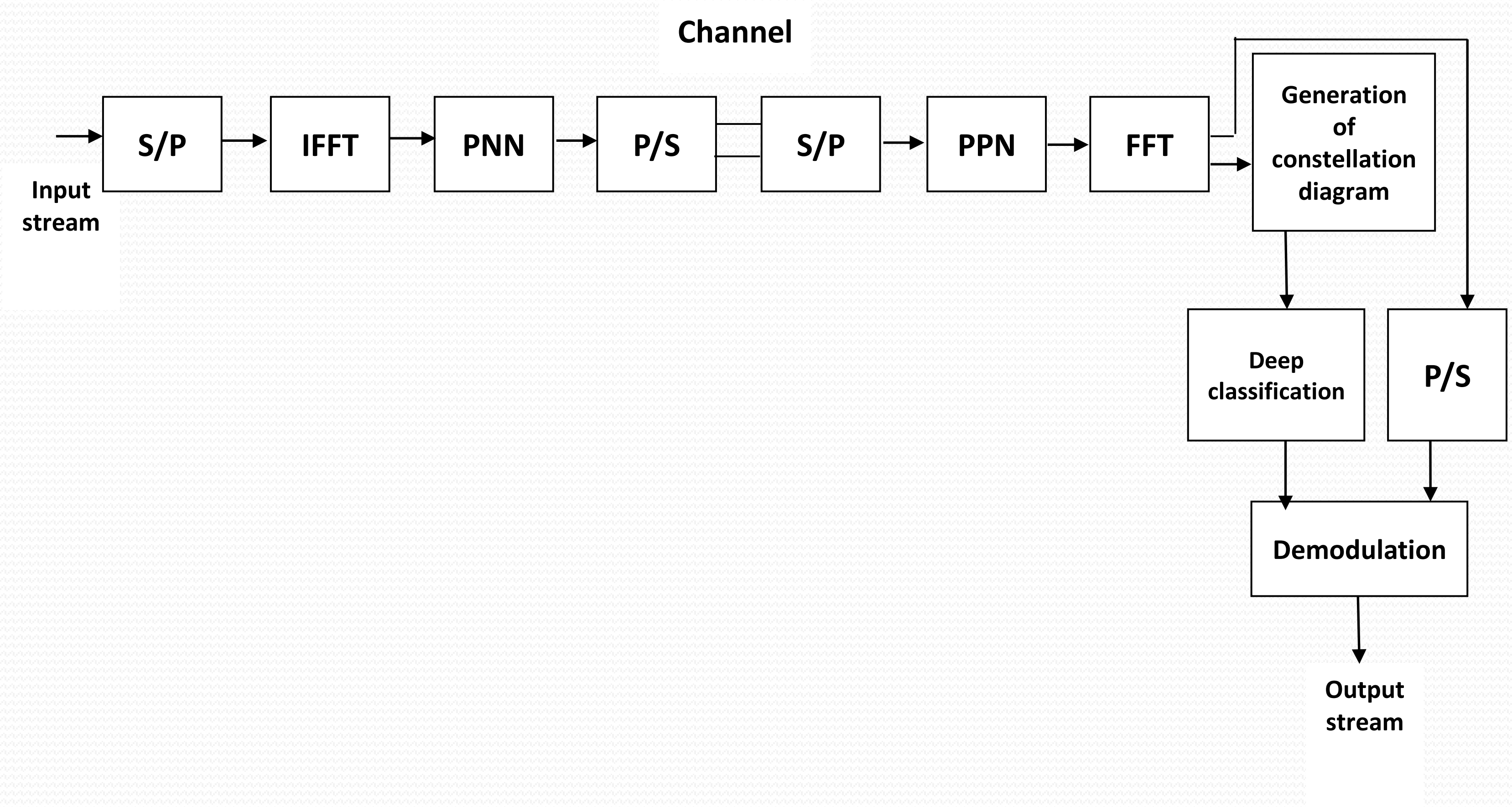
Baseband Transmission



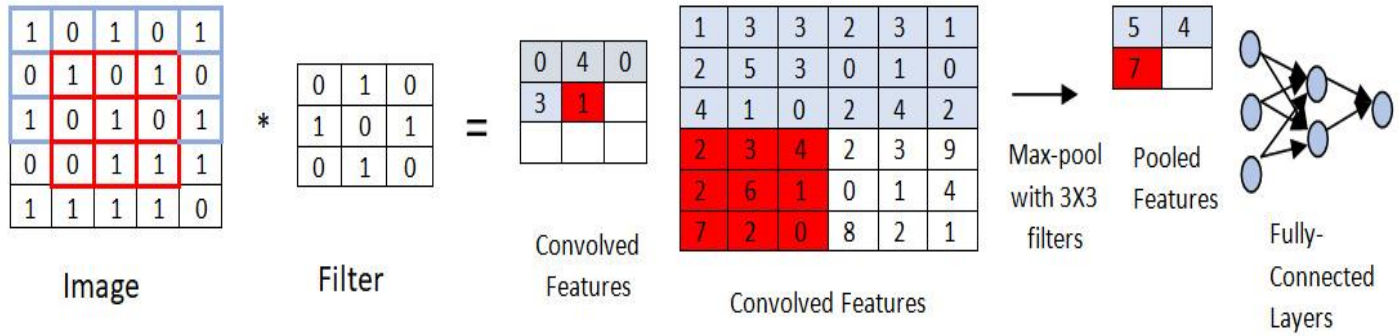
Proposed Approach

- The CNN and pre-trained network AlexNet, VGG-16, and VGG-19 are used as classifier.
- The presence of ACI that affect the original transmitted signal.
- We convert the complex signal to constellation diagram image.
- We generate 1000 images for different types of modulation at various SNRs for training.
- Pre-trained networks do not need manually features extraction.

The Proposed Classifier with Deep Learning.



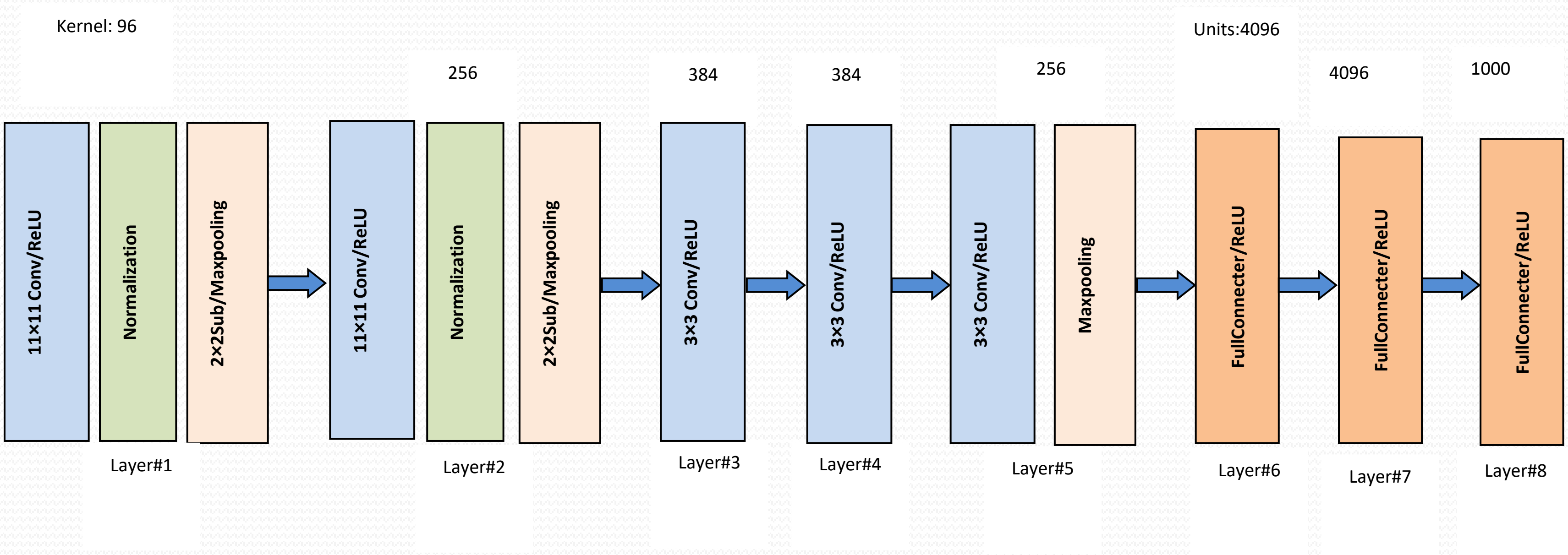
CNN based DL models



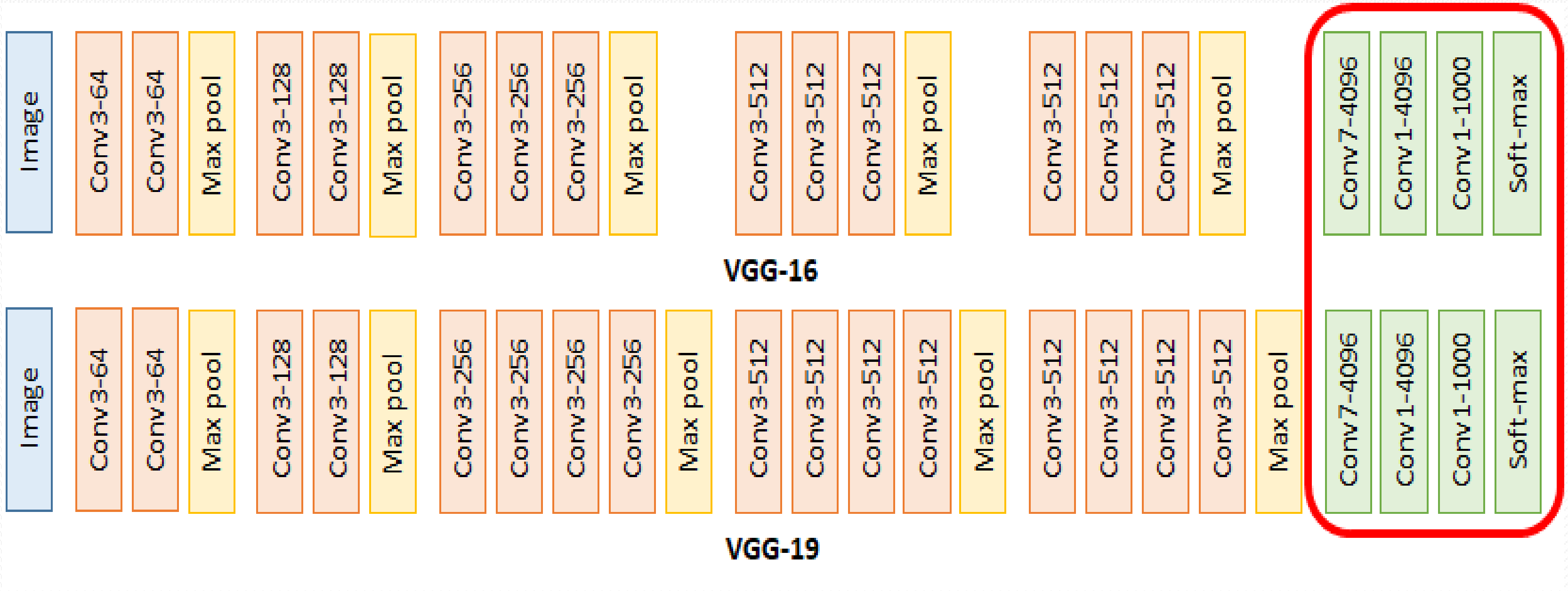
AlexNet Model

- AlexNet is a large CNN that contains of 650 thousand neurons and 60 million parameters.
- This network is designed to classify 1.2 million images into 1000 groups, and it needs a large capacity for learning.
- AlexNet contains of five convolutional layers and three fully connected layers with a 1000-way softmax layer.
- AlexNet joint several features into the network in order to improve the performance and decrease training time.
- Rectified Linear Units (ReLUs) is introduced as a neuron with non-saturating nonlinearity, with a faster training procedure.

AlexNet Model



VGG-Net Model

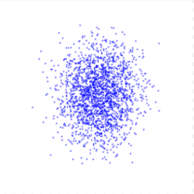
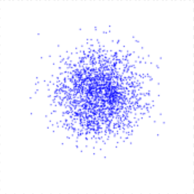
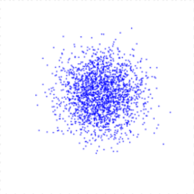
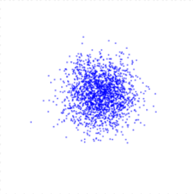
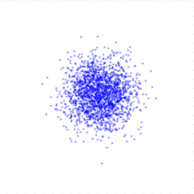
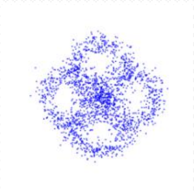
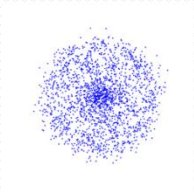
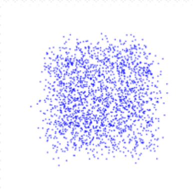
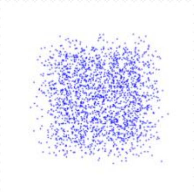
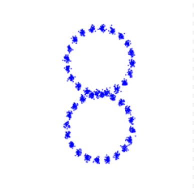
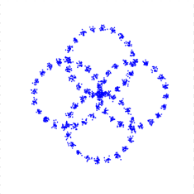
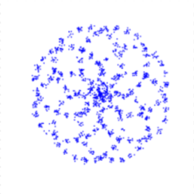
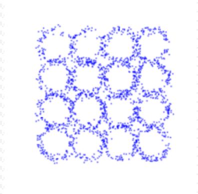
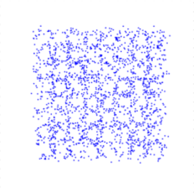


CNN for Modulation Classification

- We propose a method that used constellation diagram to converts complex sample points for the exploitation of AlexNet, VGG-16, and VGG-19.

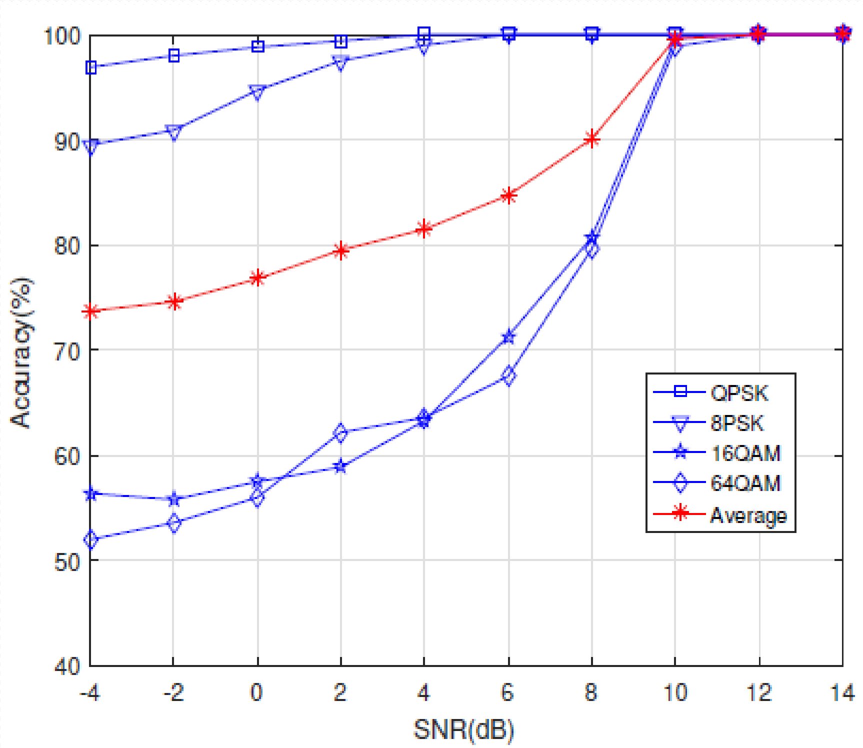
- A two-dimensional representation to the constellation diagram is used to perform the modulated signal.

Constellation Diagrams for Different Modulation Types with Different SNRs.

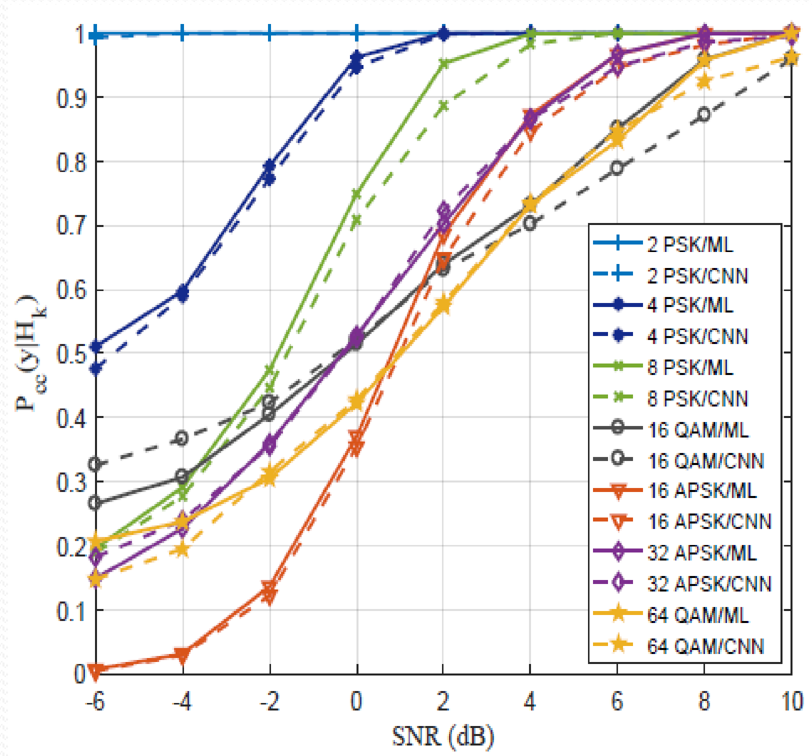
-10dB					
5dB					
20dB					
	BPSK	**QPSK**	**8PSK**	**16QAM**	**64QAM**

Previous work

CNN

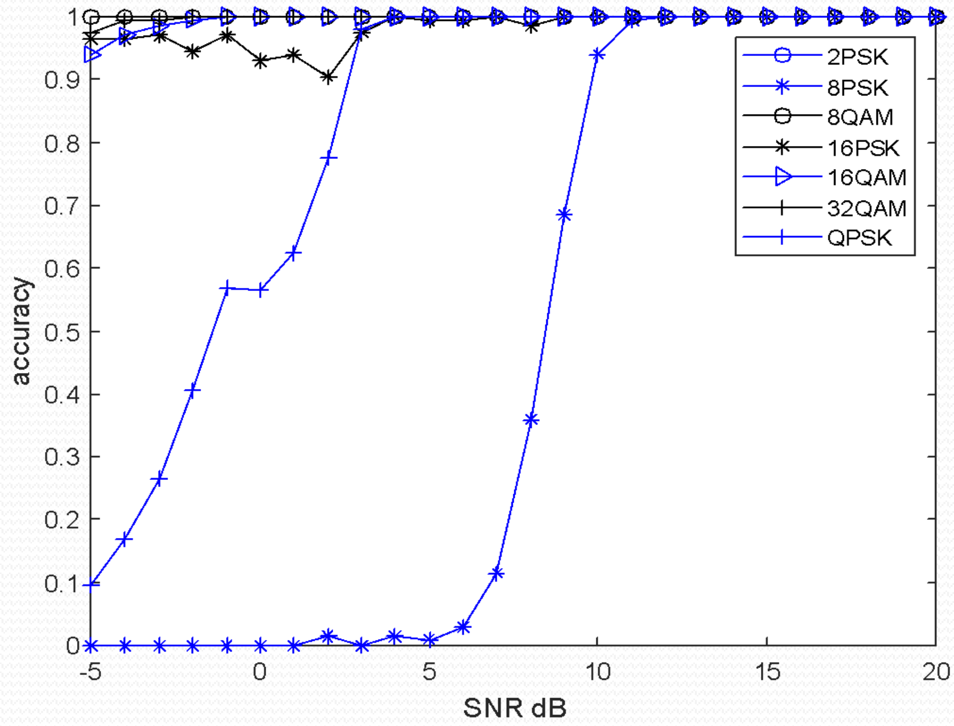


ML and CNN



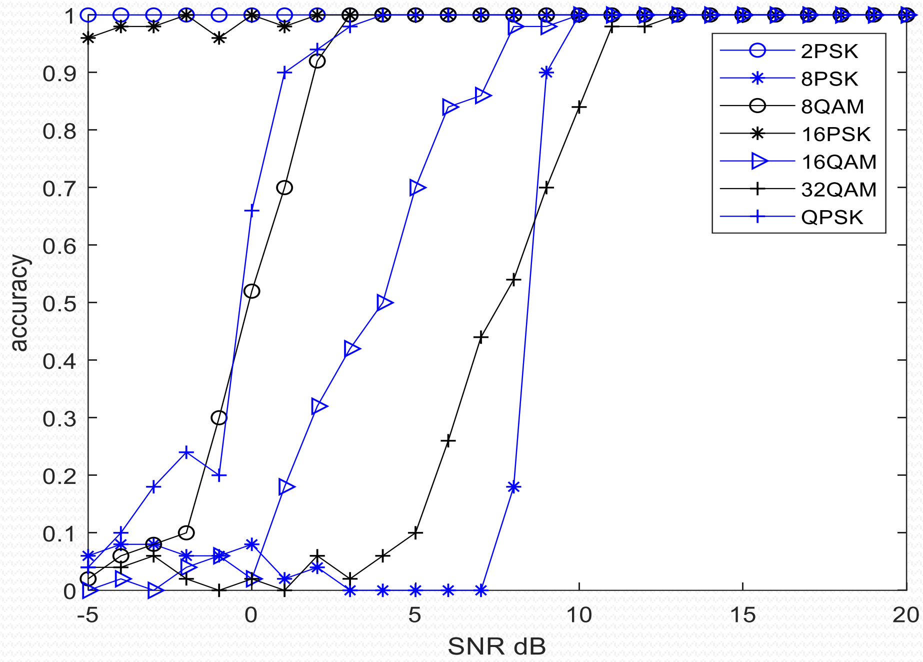
Results and Discussion

- The accuracy for AlexNet classifier for different modulation types over AWGN channel.



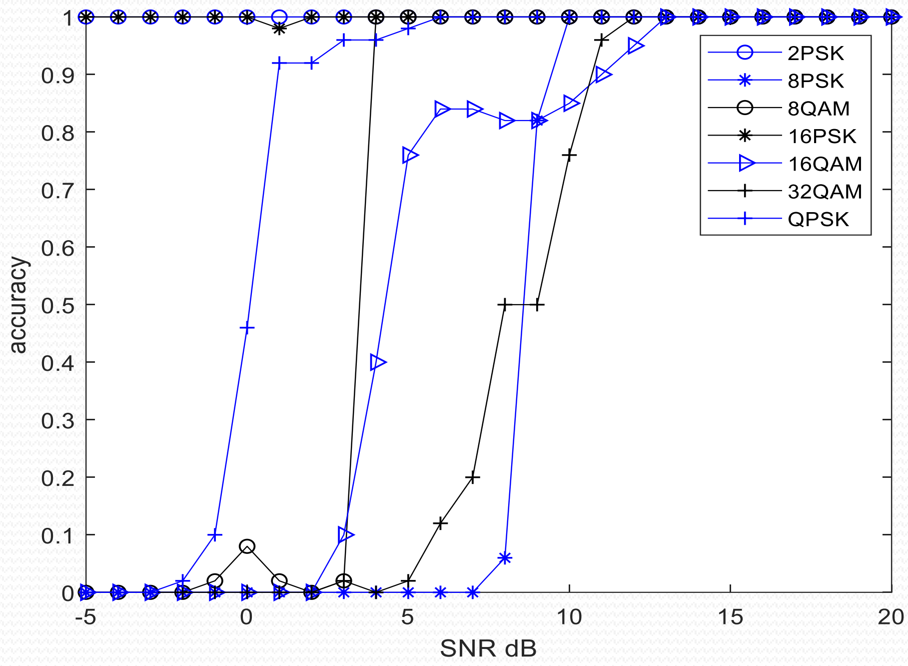
Results and Discussion

- The accuracy for AlexNet classifier for different modulation types with transmission over Rayleigh fading channel.



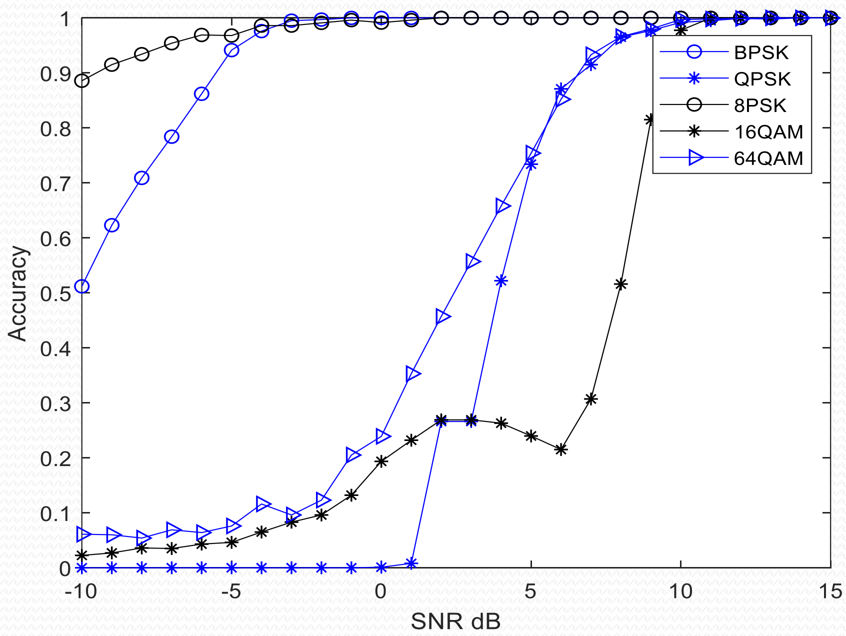
Results and Discussion

- The accuracy for VGG-19 classifier for different modulation types with transmission over Rayleigh fading channel.



Results and Discussion

- The accuracy for VGG-16 classifier for different modulation types with transmission over Rician fading channel.



Convolutional Neural Networks for Modulation Classification in FBMC Systems

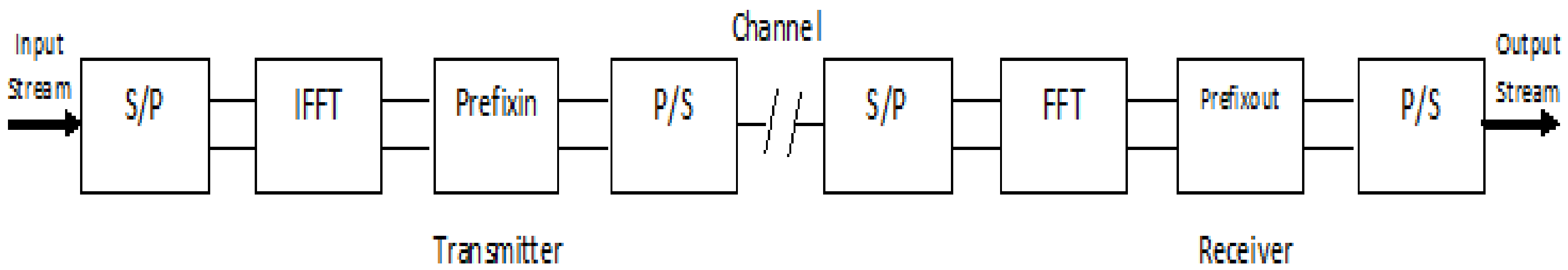
The Disadvantages of OFDM

1) Decreased spectral efficiency owing to the CP employed;

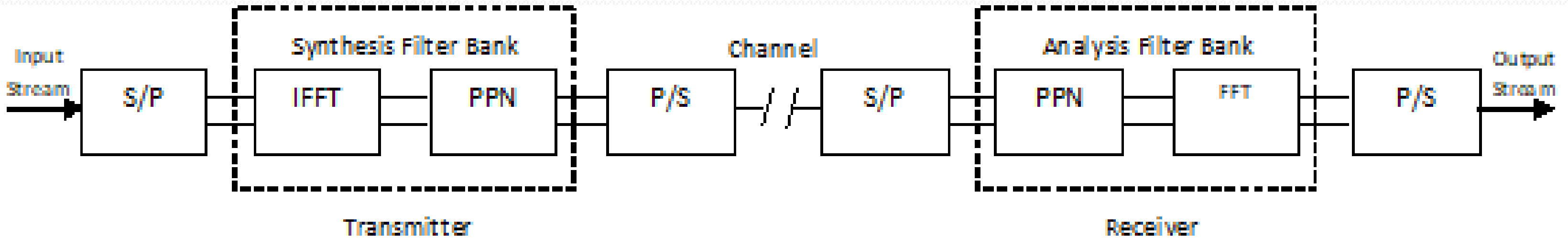
2) High spectral leakage owing to the rectangular windowing;

3) Interference amid the unsynchronized signal in the neighbouring bands.

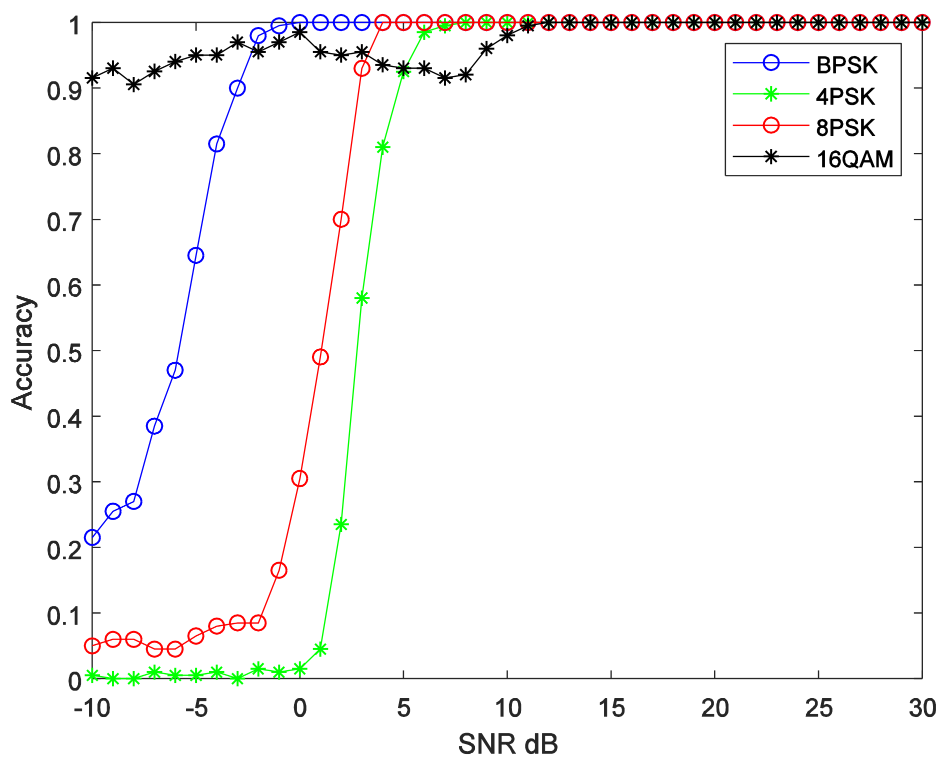
Block Diagram of Orthogonal Frequency Division Multiplexing



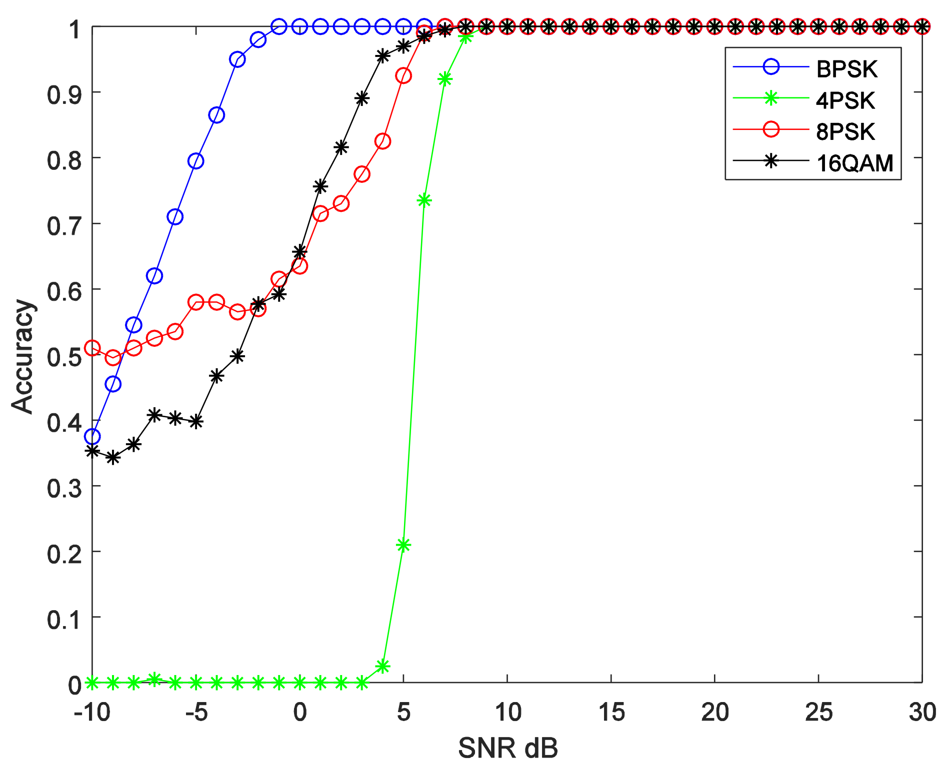
The filter bank multi-carrier (FBMC)



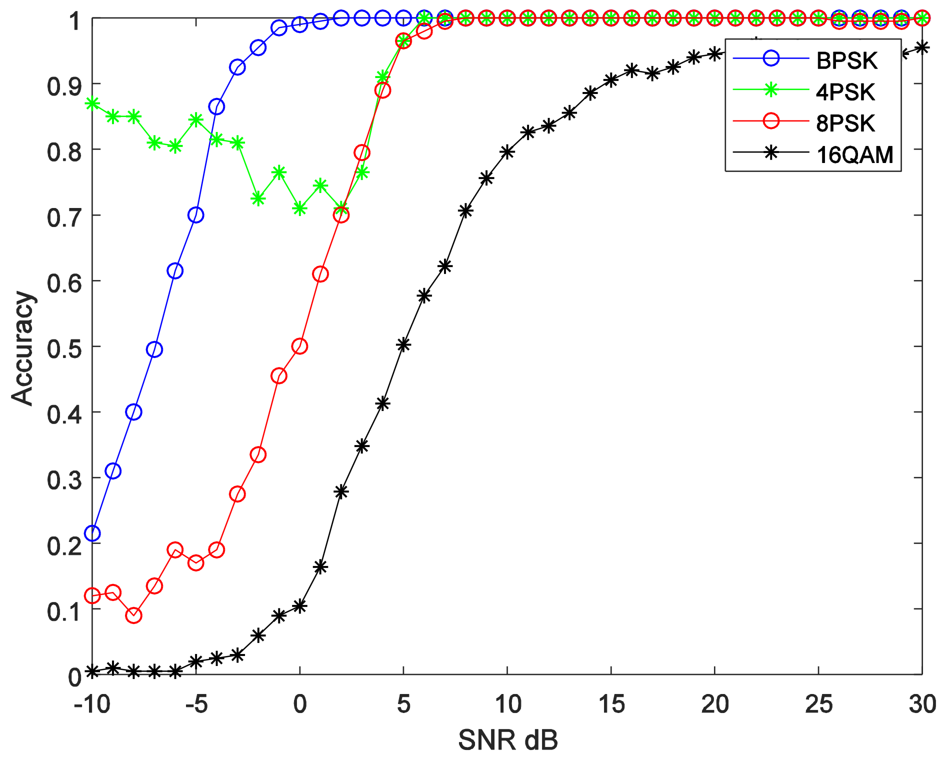
The accuracy for AlexNet classifier for different modulation types in FBMC over AWGN channel.



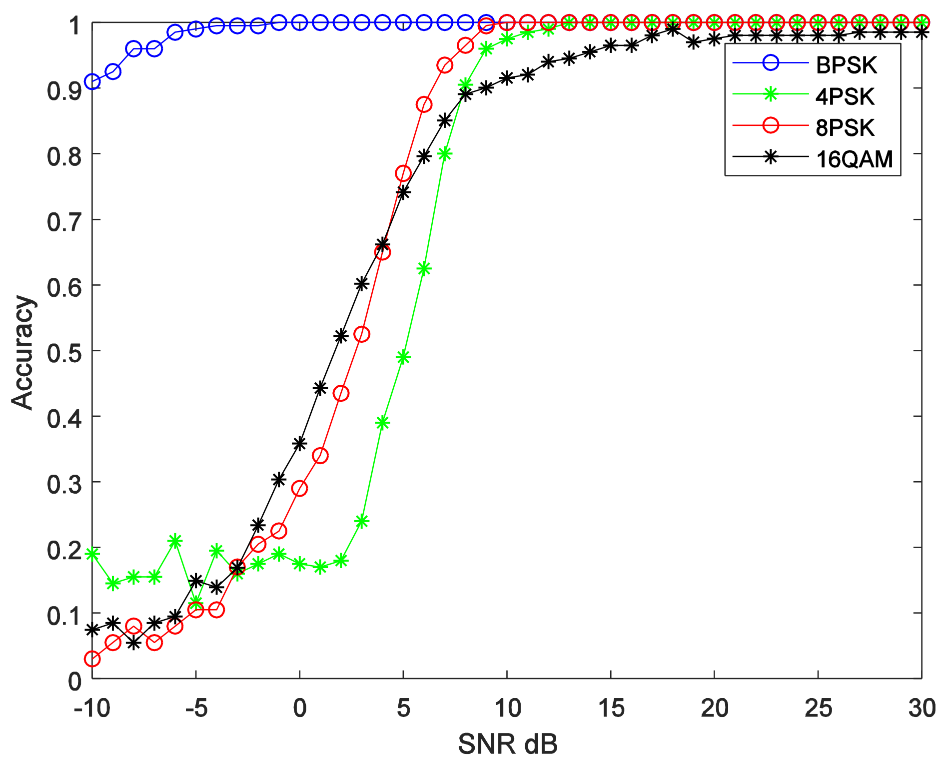
The accuracy for VGG-16 classifier for different modulation types in FBMC over AWGN channel.



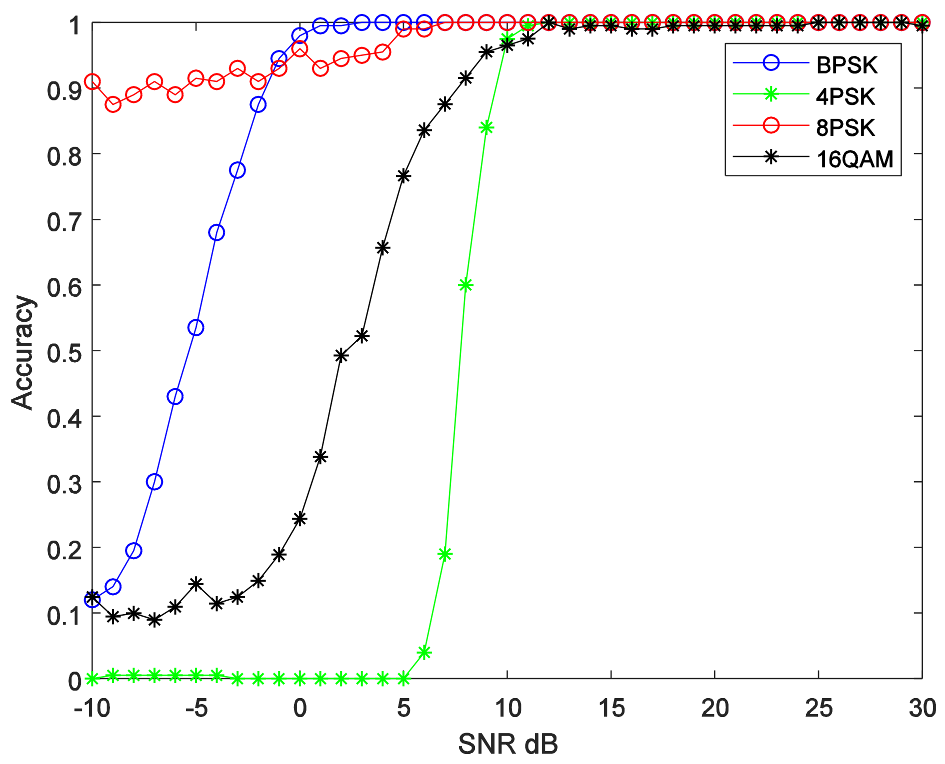
The accuracy for AlexNet classifier for different modulation types in FBMC over Rayliegh channel.



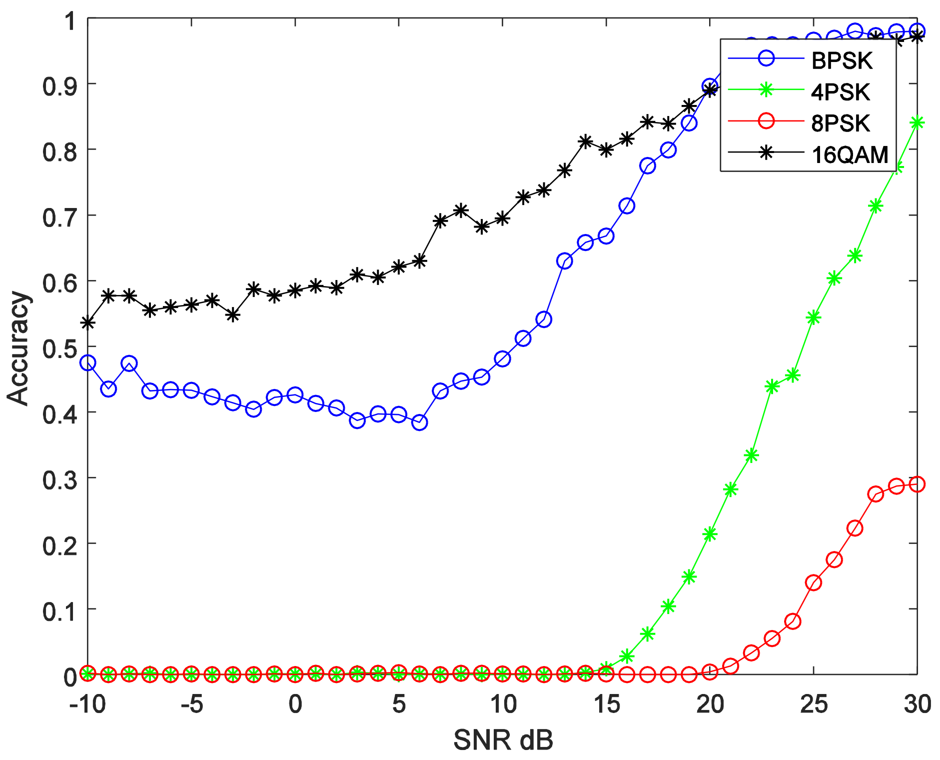
The accuracy for VGG-16 classifier for different modulation types in FBMC over Rayliegh channel.



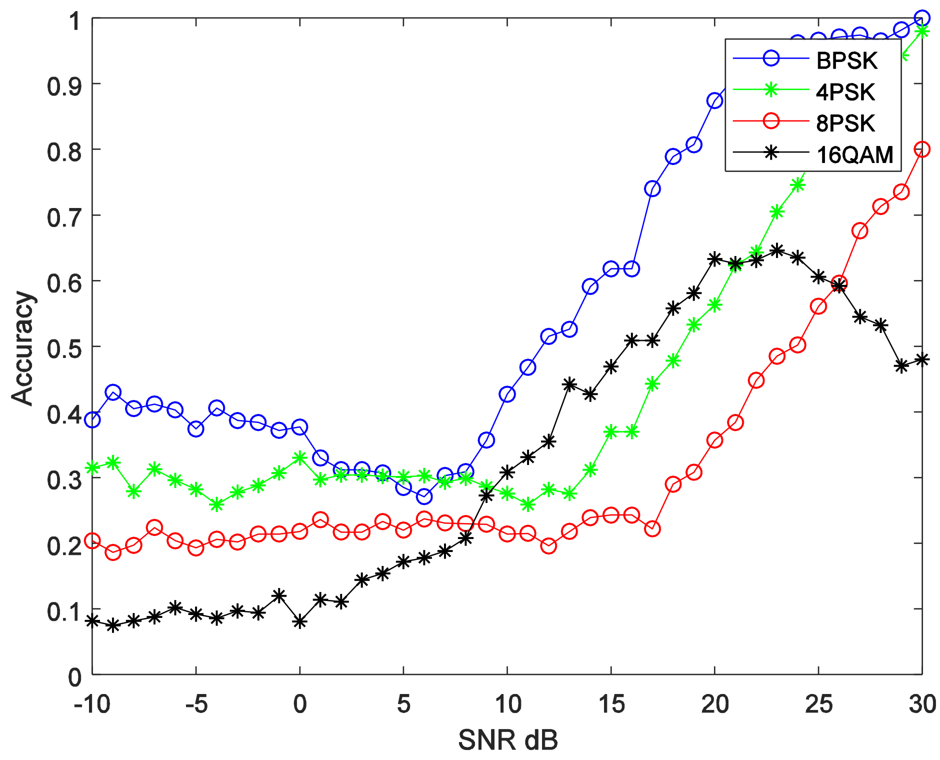
The accuracy for VGG-19 classifier for different modulation types in FBMC over Rayliegh channel.



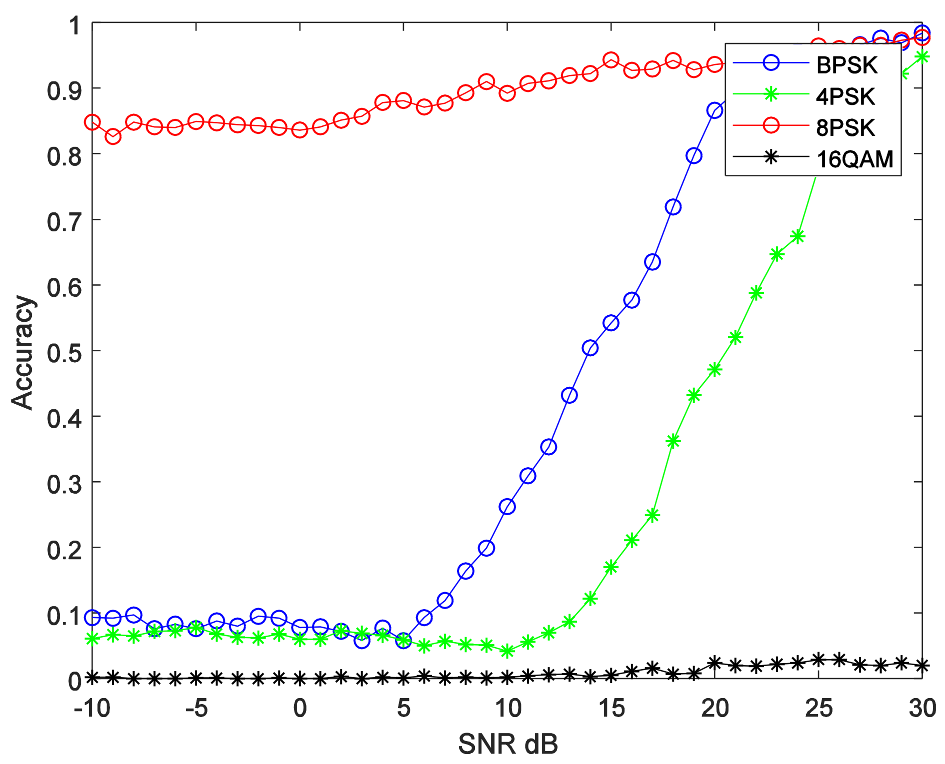
The accuracy for AlexNet classifier for different modulation types in FBMC with the pilot aided channel estimation over AWGN channel.



The accuracy for VGG-16 classifier for different modulation types in FBMC with the pilot aided channel estimation over Rayliegh channel.



The accuracy for AlexNet classifier for different modulation types in FBMC with the pilot aided channel estimation over Rician channel.



Conclusion

- An efficient method for blind classification of the STBC code in MIMO systems with the consideration of IUI was proposed. This method depends on the MUK for the signal separation and ML for code classification. The CP estimation algorithm that uses the ML does not require threshold value estimation or prior knowledge of the received signal or channel estimation.
- We propose a CNN based DL for modulation classification in wireless communication systems in the presence of ACI For training and testing, Alexnet, VGG-Net models are accepted.
- We propose a CNN based DL for modulation classification for FBMC systems.

Future Work

The future work can be suggested in the following points:

- Utilization of the proposed algorithms with non-orthogonal multiple access (NOMA) and sparse code multiple access (SCMA).
- Utilization of other methods for modulation classification based on Singular Value Decomposition (SVD) and Radon transform.
- Extension of the proposed ideas on the systems such as wireless optical communication and under water communication.
- Design of application for specific deep networks for modulation classification.

Questions?

Thanks