5
Constellation Density based Modulation Classification

5.1 INTRODUCTION

In chapter 4, the SDP of the downconverted and sampled signal is considered as a feature for modulation classification. The developed method for classification includes identification of optimum $\mathscr{L}$ and $\mathscr{G}$ as well as generation of SDP at every step of classification is little complex for real time applications. To reduce the complexity with good classification performance, constellation density matrix (CDM) based method has been developed and explained in this chapter. The density of the points in SDP is used for color image generation. Two efficient DCNN models namely ResNet-50 and Inception ResNet V2 have been employed for the classification task. The constellation signature has also been an important feature for the modulation classification problem. In this chapter, the density of the constellation is used as a feature. A CDM is formed through the local density distribution of the constellation and is used to form a color image. Three channels (RGB) of the color image are generated by masking CDM with three different masks. The classification strategy includes a three-stage hierarchical structure of DCNN based classification modules. In the first stage, the domain of the modulation schemes viz. ASK, PSK or QAM is identified and in further modules, the order of the modulation scheme is identified. For classification two DCNN, ResNet-50, and Inception ResNet V2 have been used. For a wide range of SNR, signals are generated using LabVIEW, and color images formed with these signals are used for training and testing of the method [Kumar *et al.*, 2020b].

5.2 DEEP LEARNING FOR MODULATION CLASSIFICATION

Deep Networks consist of multiple layers with multiple neurons in each layer for the extraction of features autonomously. Initial layers extract abstract features, and deep layers get significant features by multiple nonlinear transformations on the previous layer's output. DL models extract these features without manual intervention, and it is called data-driven feature extraction.

5.2.1 ResNet-50

ResNet-50 is well known DL model in the field of image classification. Deep networks provide good classification results in comparison to shallower, but these are difficult to train due to the vanishing gradient problem. This problem has been resolved by incorporating residual function [He *et al.*, 2016] and three-layered bottleneck residual architecture, as shown in Figure 5.1(h). For the given input x_{l-1}, mapping of a function $x_l = H(x_{l-1})$ is done using function $F(x_{l-1}) = H(x_{l-1}) - x_{l-1}$, where $F(x)$ is residual function. The bottleneck structure of residual architecture effectively reduced the computational complexity of the network, and the shortcut path eliminates the vanishing gradient problem. The pooling of features is used to reduce the distortion effect along with computational complexity. For this purpose mainly two types of pooling functions have been used. After the first convolution layer, max-pooling is done to extract initial low-level features, and after the last convolution operation, average pooling is used as all the final extracted features are equally important for decision making. Rectified Linear Unit (ReLU) activation function: $r(x) = max(0,x)$ has been used instead of traditional, for fast training process.

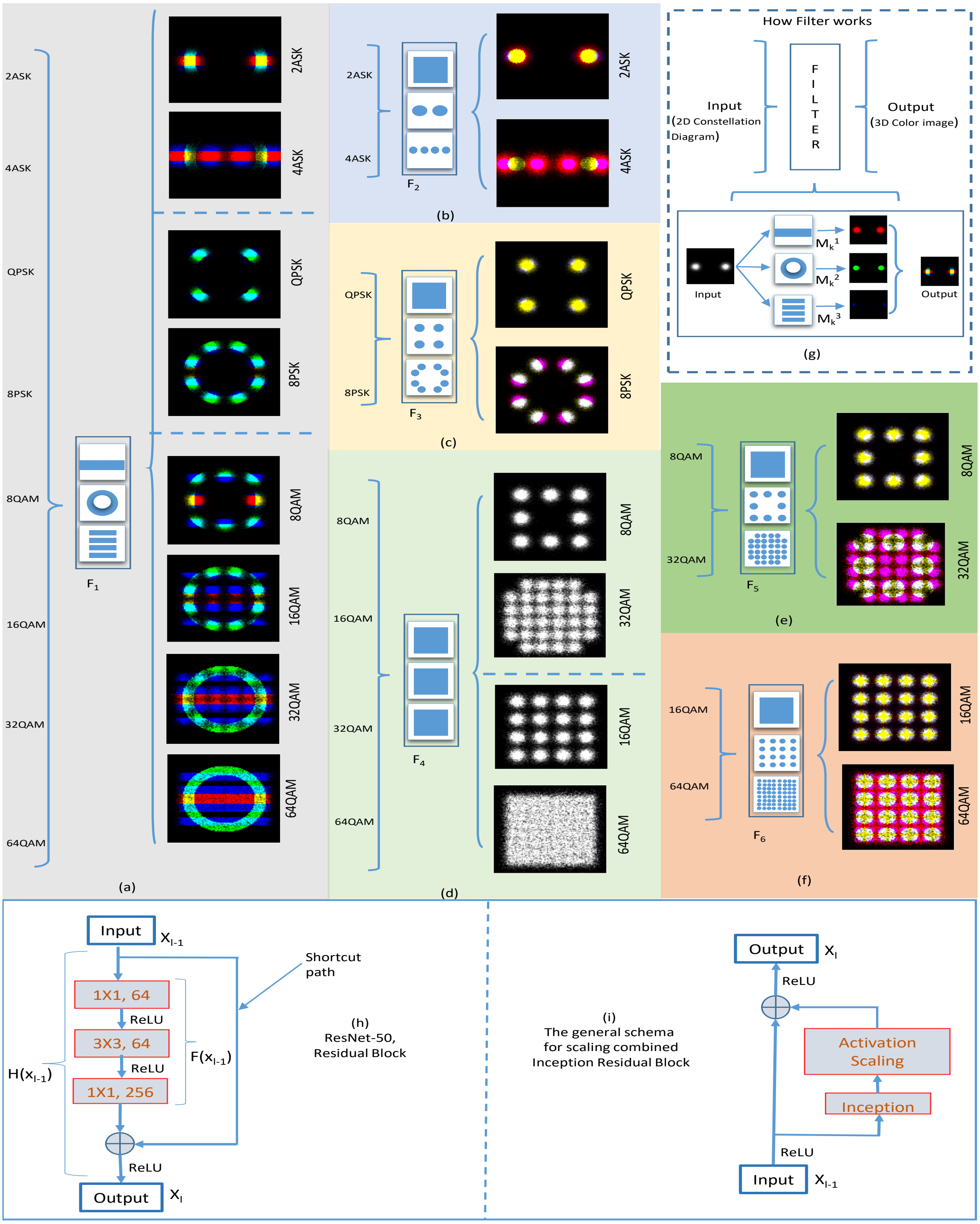

Figure 5.1 : A three-stage modulation classification procedure for eight modulation schemes with masking filters is shown. First stage : (a) Constellation of all modulation schemes are filtered through F_1 and classified into three groups. Second stage : (b) Constellation of 2ASK and 4ASK are filtered through F_2 and classified, (c) Constellation of QPSK and 8PSK are filtered through F_3 and classified, (d) Constellation of 8QAM, 16QAM, 32QAM and 64QAM are filtered through F_4 and classified into two groups. Third stage : (e) Constellation of 8QAM and 16QAM are filtered through F_5 and classified, (f) Constellation of 32QAM and 64QAM are filtered through F_6 and classified. (g) Description of the working procedure of all five filters. Functional architecture of (h) ResNet-50 Residual Block, and (i) Inception Residual Block.

In addition, the regularization method called *dropout* has also been applied with 0.5 probability to eliminate overfitting for training data.

5.2.2 Inception ResNet V2

Inception ResNet V2 network is an extensive and efficient network in image classification. The configuration of *Inception Residual Block* is shown in Figure 5.1(i). Where inception block is a sub-network of traditional parallel-connected convolution layers, followed by batch normalization and activation layers. The computation complexity has been significantly reduced by introducing 1×1 filters at the earlier layers, and then larger filters in *Inception Block* [Szegedy *et al.*, 2016]. For residual summation, *Activation Scaling* is required to compensate for the dimension reduction done by *Inception Block*. This model has parallel branches, which are easy to get trained on multiple GPUs. A very deep and wide inception network is implemented with intermediate auxiliary classifiers to reduce the vanishing gradient problem while back-propagation. For neuron activation, the ReLU function is used, and for regularization, *dropout* with a probability of 0.5 is used similar to ResNet-50.

5.3 DATA PRE-PROCESSING AND TRAINING

This research aims to identify the correct modulation scheme among 2ASK, 4ASK, QPSK, 8PSK, 8QAM, 16QAM, 32QAM, and 64QAM. The constellation points are used to generate CDM and transformed into a color image with three channels generated by masking the CDM with a proper filter. Generated color images are used to train multiple DL models in three stages of the classification hierarchy.

5.3.1 Color Image Formation using CDM

The signal has been transformed into a color image of size $3\times100\times100$, to facilitate both the considered models with striking features. After normalizing the constellation points with average energy, points in the 4×4 area of the complex plane are considered for further processing. This range covers most of the points for SNR under consideration. Constellation is divided into 100×100 equal grid sections. The number of points in each section is calculated and scaled in the (0,255) range. The 100×100 dimension matrix formed is CDM. To convert CDM into a color image, filter F_k is applied, where $k \in \{1,2,...,6\}$. F_k consists of three masks M_k^1, M_k^2 and M_k^3, as shown in Figure 5.1(g). Each mask is a Boolean matrix of dimension 100×100 with distribution according to Table 5.1. It has Boolean '1' at different shapes provided, and the remaining elements of the matrix are valued Boolean '0'. The output of each mask represents one channel of the RGB image. Output of m^{th} mask of F_k filter is given by

$$CDM(i,j) \bullet M_k^m = \begin{cases} CDM(i,j) & ; \quad M_k^m = 1 \\ 0 & ; \quad M_k^m = 0 \end{cases}$$

5.3.2 Classification Strategy

The hierarchy of three stages is used to classify a modulation scheme. In the first stage, the domain of modulation is identified in two steps. (1) CDMs of all modulation schemes for a range of SNR are filtered through F_1 to get color images. F_1 has a set of three masks, the first mask has a shape of a rectangular strip that covers all points of the ASK constellation, the second has a shape of a circular strip to cover points of the PSK constellation, and the third has four rectangle strips to cover the points of QAM constellation. Color images generated from CDMs of all modulation schemes filtered through F_1 are shown in Figure 5.1(a). (2) These images are given as an input to the DL model for three-class classification. In the second stage of the classification hierarchy, three filters F_2, F_3, and F_4 are used to generate color images. If decision of first stage is in favour of ASK

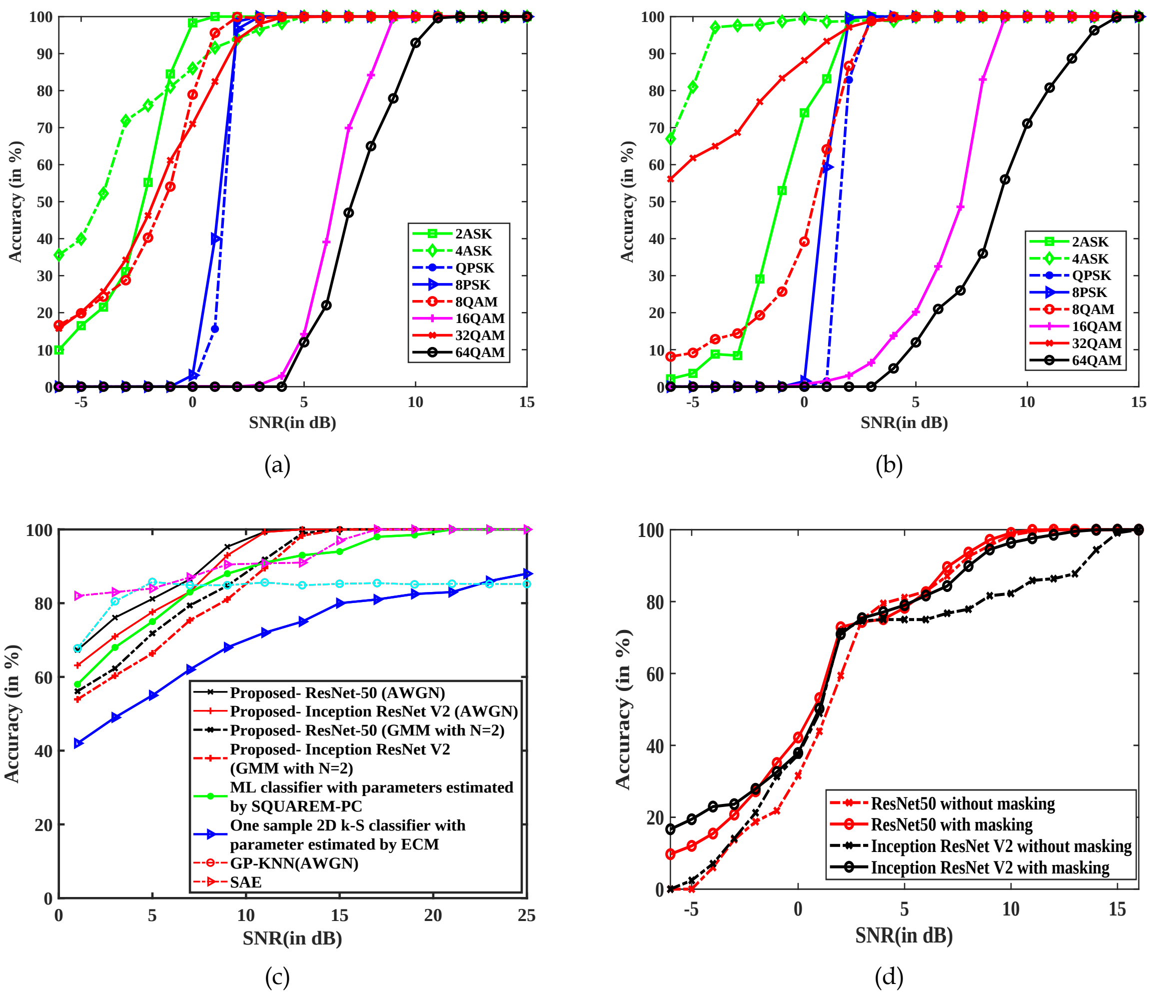

Figure 5.2 : Accuracy of developed method with (a) ResNet-50 and (b) Inception ResNet V2 for eight modulation schemes. (c) Proposed method comparison with GP-KNN in AWGN, ML classifier with parameter estimated by SQUAREM-PC in GMM (N=2) and one sample 2D K-S classifier with parameter estimated by ECM in GMM (N=2) for 2ASK, QPSK, 8PSK, and 16QAM modulation schemes. (d) Comparison of average classification accuracy with and without masking filters for ResNet50 and Inception ResNet V2.

domain, filter F_2 is used to filter CDMs of 2ASK and 4ASK constellations, for PSK domain F_3 is used to filter CDMs of QPSK and 8PSK constellations, and for QAM domain F_4 is used to filter CDMs of 8QAM, 16QAM, 32QAM and 64QAM constellations as shown in Figure 5.1(b), 5.1(c) and 5.1(d) respectively. In the third stage, 8QAM and 32QAM are classified with a binary classifier and remaining 16QAM and 64QAM with another binary classifier, where these classifiers are trained with color images generated through F_5 and F_6 as shown in Figure 5.1(e) and 5.1(f) respectively. The description of dimensions used for all six filters is given in Table 5.1, where each dimension depicts one grid section.

5.3.3 Model Implementation and Training

Pre-trained models of both ResNet-50 and Inception ResNet V2 architectures take an input image of size $3\times100\times100$ and classify for 1000 classes. In this work, binary and three-class classification task is performed by concatenating 8 fully connected layers at the end of each model. Starting 7 layers out of these 8 layers contains 1000, 750, 500, 250, 100, 50, 20 neurons, and the last layer contains 2 or 3 neurons according to the selected classifier. For training, -4 dB to 30 dB SNR with the step of 1 dB and 35 dB to 70 dB SNR with the step of 5 dB is considered, and 50 images at each SNR (2150 images in total) have been generated for each modulation scheme. In the first step of classification, the considered eight modulation schemes are divided into three groups, and 17200 (8×2150) images are given for training. In the second step, 2ASK and 4ASK have been classified with the model trained with 4300 images. Similarly, the hierarchy has been followed for the final classification. Both models are implemented in python with Keras libraries, and NVIDIA DGX-2 GPU has been used to train the models. Parameters of the solver configuration have also been adjusted for better classification and fast training processes, such as the learning rate is 0.0001, and the mini-batch size is 64. Batch size is considered based on the computation efficiency of GPU.

5.4 RESULTS AND DISCUSSION

In this section, the performance of ResNet-50 and Inception ResNet V2-based methods for the classification of eight modulation schemes are shown. The classification has been done in three stages, and probabilities of correct classification in consecutive stages are multiplied for final probability.

Modulation classification accuracy for considered modulation schemes is shown in Figure 5.2(a) and 5.2(b) for ResNet-50 and Inception ResNet V2 models respectively. Results are obtained for 1000 signal realizations, each signal containing 50k symbol points. Both the models, ResNet-50 and Inception ResNet V2 provide reliable classification above 5 dB SNR for all modulation schemes except 16QAM and 64QAM. In comparison to all other modulation schemes, the classification accuracy of 16QAM and 64QAM is less, as both get confused with each other in their final stage of classification.

In Figure 5.2(c), classification accuracy comparison of the proposed method with GP-KNN in the AWGN environment is given for BPSK, QPSK, 8PSK, and 16QAM modulation schemes. The proposed method achieves greater accuracy than GP-KNN for SNR higher than 7 dB. The proposed method is also compared with an ML classifier and one sample 2D K-S classifier in Gaussian Mixed Model (GMM) with N=2, given in [Chen *et al.*, 2019]. The proposed method with ResNet50 and Inception ResNet V2 models performs better than ML classifiers for 7 dB and above SNR. Also, the proposed method works better than one sample 2D K-S classifier for all values of SNR. All comparisons are done for 512 symbols.

To show the effect of masking filters, results without masking filters are also generated using the same hierarchy and channel condition for comparison as shown in Figure 5.2(d).

Table 5.1 : Fiters specifications

	R Channel	G Channel	B Channel
Filter1	Rectangle: (11X100)	Disc: R1=27; R2=37	4 Rectangle: (9X100)
Filter2	Square: (100X100)	2 Circles: R=8	4 Circles: R=6
Filter3	Square: (100X100)	4 Circles: R=18	8 Circles: R=10
Filter4	Square: (100X100)	Square: (100X100)	Square: (100X100)
Filter5	Square: (100X100)	8 Circles: R=10	16 Circles: R=6
Filter6	Square: (100X100)	32 Circles: R=8	64 Circles: R=4

Performance gain in accuracy is achieved for both models. Reasons for accuracy improvement are discarding the noisy constellation points by masking filters, and color image generation with three masks, each containing information of one class.

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