Robust Automatic Modulation Classification Using RGB Density-Based Constellation Diagram Decomposition

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***Abstract*—Automatic Modulation Classification (AMC) is a fundamental component of adaptive and cognitive radio systems, enabling spectrum awareness and interference management. Recent deep learning approaches based on constellation representations have achieved promising performance; however, their effectiveness is highly sensitive to preprocessing choices, particularly histogram normalization, which can distort signal density information and hinder neural network convergence. This paper proposes a robust RGB constellation representation derived from two-dimensional histograms of IQ samples, where density information is encoded using a color map to form a structured multi-channel input. This representation is combined with a lightweight convolutional neural network based on separable convolutional layers, enabling efficient feature extraction while maintaining low computational complexity. The proposed method is evaluated on the CSPB.ML.2018 dataset under realistic impairments, including carrier frequency offset, phase rotation, and additive noise. Experimental results show that the proposed representation significantly improves convergence and classification performance, increasing accuracy from 12.5% to 88.5% under realistic impairment conditions. These results demonstrate that RGB density-based constellation representations provide a robust and computationally efficient solution for practical AMC systems.**

***Index Terms*—AMC, AMR, automatic modulation recognition, classification, cognitive radios, constellations, CNN, decomposition, fusion, green AI, vector diagram.**

I. Introduction

Automatic Modulation Classification (AMC) is a key component of modern wireless systems, enabling spectrum awareness and adaptive operation without prior knowledge of the transmitted signal. Recent advances in deep learning have significantly improved AMC performance by allowing data-driven feature extraction directly from signal representations. Among the various input formats, constellation diagrams provide a compact and physically meaningful representation of modulation characteristics. When combined with convolutional neural networks (CNNs), they enable efficient spatial feature learning with relatively low computational complexity. However, constellation-based approaches remain highly sensitive to preprocessing choices, particularly histogram normalization. In impaired conditions (e.g., noise, carrier frequency offset), normalization may suppress relevant density information or introduce unstable representations, leading to poor convergence and degraded performance. This work investigates the role of representation conditioning in constellation-based AMC. We propose a density-based RGB representation derived from two-dimensional histograms of IQ samples, where a fixed nonlinear colormap maps scalar densities into a three-channel space. Importantly, this transformation does not introduce additional physical information. Instead, it acts as a structured nonlinear embedding that reshapes the input distribution into a form that is more amenable to learning, particularly for lightweight CNN architectures. The proposed representation is combined with a compact CNN using separable convolutions and evaluated under realistic impairments. Results show that, while gains are modest in nominal conditions, the RGB representation significantly improves robustness and convergence in challenging scenarios.

The main contributions of this paper are summarized as follows: We evaluate constellation-based AMC across multiple preprocessing stages and show that histogram normalization critically affects performance. We propose a density-preserving RGB mapping of IQ histograms as a form of signal surface augmentation [1], improving robustness and convergence.

This paper reviews the state of the art in AMC in Section II, with a particular emphasis on learning-based and constellation-driven approaches. The proposed methodology is presented in Section III, while constellation representations and experimental setup are described in Sections IV and V. Finally, performance evaluation and discussion are provided in Section VI.

II. State of the Art

Automatic modulation classification has been extensively studied, with a transition from feature-based methods to deep learning approaches in recent years. Surveys such as [2]–[4] highlight the effectiveness of CNNs and other neural architectures for AMC tasks. Constellation-based representations have gained attention due to their intuitive structure and compatibility with image-based models. Early work [5] uses grayscale histograms of IQ samples combined with CNNs, demonstrating strong performance with relatively simple architectures. Extensions to multi-channel representations have also been explored. For instance, [6] converts constellations into three-channel images to leverage standard CNN architectures, although without explicitly analyzing the role of the mapping itself. Other approaches incorporate additional preprocessing to enhance features prior to classification. In [7], Gabor filtering and thresholding are applied to constellation diagrams to generate multi-channel inputs. While effective, such methods introduce additional computational complexity and rely on handcrafted processing steps whose advantage over learned CNN features is not always clear. In contrast to prior work, this paper focuses on the role of representation itself rather than increasing model complexity. Specifically, we investigate how a fixed nonlinear mapping of histogram densities into an RGB space affects learning behavior. Unlike methods that aim to inject new information, the proposed approach preserves the original density content while improving its conditioning for CNN-based classification.

III. Information flow, Generator and Dataset

A. Information flow

The overall information flow of the proposed system is illustrated as follows. The incoming complex in-phase and quadrature (IQ) samples received by the transceiver first undergo a set of pre-processing steps, including demodulation and signal correction stages, whose configuration depends on the evaluated model. The processed IQ data are then mapped onto a constellation diagram, represented either as a greyscale histogram or as a multi-channel RGB density image. This image representation is subsequently used as input to a convolutional neural network, which is trained to automatically classify the underlying modulation scheme.

B. Dataset

Experiments are conducted on the CSPB.ML.2018 dataset [8], which includes eight digital modulation schemes under controlled impairments such as CFO, phase rotation, and additive noise. Each signal contains 32,768 IQ samples. A noise-free version is used for training, while impaired versions are used for evaluation. Optional preprocessing steps (e.g., CFO correction, noise injection) are applied to simulate realistic conditions.

C. Generator

A custom data generator is used to construct training samples on the fly from stored complex baseband signals. For each example, raw IQ samples are loaded and optionally processed through a sequence of signal conditioning steps, including carrier frequency offset correction, rational resampling, and root raised cosine filtering. Depending on the selected mode, the generator either retains the full waveform or performs symbol rate sampling with configurable timing selection. Additional impairments, including random phase rotation and additive white Gaussian noise, can be applied to simulate channel variability. The resulting complex signal is then mapped to an image representation using a fixed histogram based RGB mapping and returned together with the corresponding label. This design allows systematic enabling or disabling of individual processing stages in order to study their impact on model performance. The overall structure of the methodology is illustrated in Fig. 1.

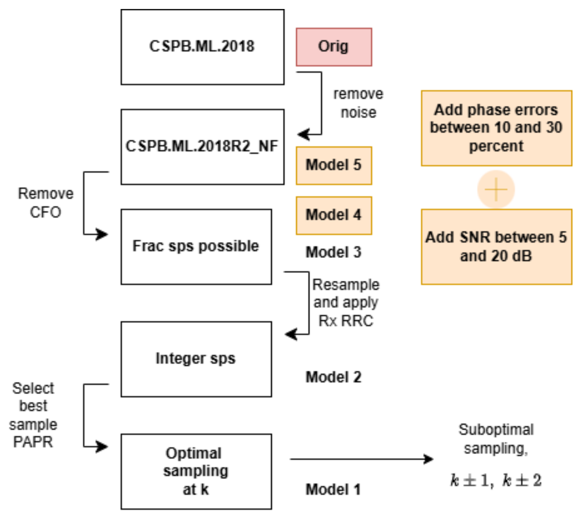

Fig. 1: Overall data-flow diagram depending on the used model

All models operate on the complete waveform, ensuring that all symbol samples are used without selecting specific sampling instants. The original noisy CSPB.ML.2018 dataset, denoted as Orig (for original dataset), is used as a baseline for comparison. All modified versions are derived from the noise free CSPB.ML.2018_NF dataset. Model 2 applies carrier frequency offset (CFO) correction, resampling, and matched root raised cosine filtering. Model 3 applies only CFO correction. Model 4 extends Model 3 by introducing additional phase shifts and AWGN with signal to noise ratio values ranging from 5 to 20 dB in steps of 5 dB. Finally, Model 5 follows the same procedure as Model 4 but without CFO correction.

D. Neural Network Models

All models share the same lightweight architecture, composed of two convolutional layers followed by a flattening operation and a fully connected classifier. Two variants are considered: a baseline CNN operating on single-channel grayscale histograms, and a CNN operating on three-channel RGB representations. ReLU activations are used in hidden layers, dropout is applied after convolutional layers, and softmax is used in the output layer. Training is performed using the Adam optimizer.

IV. Constellations

Constellation diagrams are generated by mapping IQ samples onto a two-dimensional histogram, where each waveform produces a single representation. The IQ plane is discretized into a 128×128 grid, and each bin encodes the local sample density.

Two representations are considered:

Grayscale: the histogram is used as a single-channel image, where pixel intensity is proportional to bin counts. Two common normalization techniques are evaluated.

These grey scale constellation matrices are used as inputs to the neural network. An example corresponding to a BPSK signal from the dataset is shown in Fig. 2.

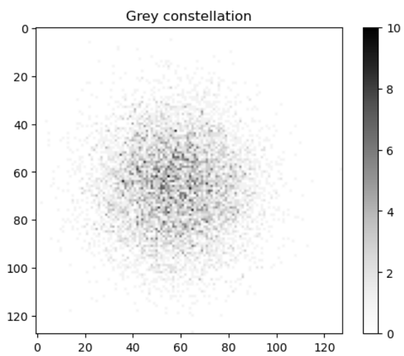

Fig. 2: Grey constellation of a BPSK signal with noise and CFO

RGB: the histogram is normalized and mapped to a three-channel image using a fixed colormap (Turbo), where colors represent density levels, ranging from low-intensity (blue) to high-intensity (red).

This mapping preserves the original density information while embedding it into a higher-dimensional space. No additional information is introduced, instead, signal surface augmentation [1] is achieved through color encoding.

Examples of RGB constellation diagrams for BPSK, QPSK, 8PSK, and 16QAM signals at an SNR of approximately 8 dB are shown in Fig. 3.

V. Discussions and Experimental Tests

A. About the importance of normalization

IQ samples are mapped onto two dimensional histograms to form constellation like representations. A common approach is to normalize each histogram by the total number of samples (L1 normalization), producing a probability mass function. While this bounds the dynamic range, it removes density information that is correlated with signal to noise ratio. Under low SNR conditions and impairments such as carrier frequency offset, histograms become sparse and diffuse, and L1 normalization further reduces inter bin contrast. This can lead to unstable training or complete failure to converge. This observation highlights that, while normalization can improve numerical stability, excessive normalization may suppress physically meaningful information required for learning, particularly when histogram sparsity and non stationary impairments are present. To analyze this effect, two normalization strategies are evaluated. L1 normalization emphasizes the

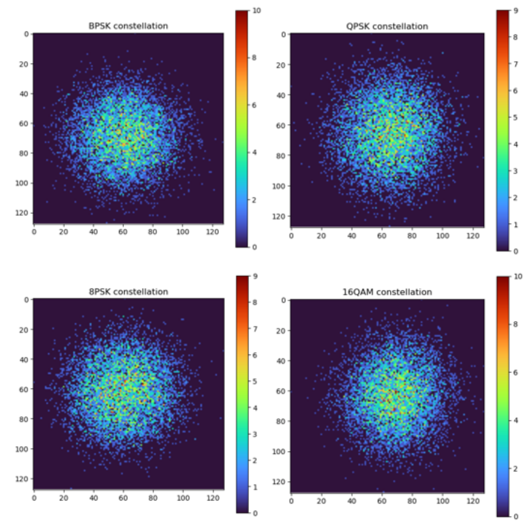

Fig. 3: Example of RGB constellation representations.

global distribution. The second applies a logarithmic compression followed by max normalization, in which a $\log(1+\cdot)$ transform reduces the dynamic range of bin counts and the result is scaled by the maximum histogram value to constrain the representation to the range [0,1]. These normalizations emphasize different properties of the data, namely global distribution versus local intensity structure. For the RGB representation, max normalization is applied prior to color mapping. This conversion is done automatically by converting into an image. This ensures a consistent dynamic range while preserving relative density structure, which is then encoded into a three channel image using a fixed colormap.

Let $H \in \mathbb{R}^{N \times N}$ denote a two dimensional histogram whose entries $H_{i,j}$ represent the number of samples falling into the (i, j)th bin. A small constant $\epsilon > 0$ is added to the denominators to ensure numerical stability.

The L1 normalized histogram is defined as

$$H_{\mathrm{L1}} = \frac{H}{\sum_{i,j} H_{i,j} + \epsilon}. \tag{1}$$

The logarithmically normalized histogram is defined as

$$H_{\log} = \frac{\log(1 + H)}{\max_{i,j} \log(1 + H_{i,j}) + \epsilon}. \tag{2}$$

For the RGB representation, max normalization is applied as

$$H_{\mathrm{rgb}} = \frac{H}{\max_{i,j} H_{i,j} + \epsilon}, \tag{3}$$

where the resulting values are mapped to a three channel RGB image using a fixed colormap.

B. Information Leakage Considerations

Constellation-based AMC using CNNs is sensitive to data leakage when image representations encode artefacts unrelated to the underlying modulation physics. Some correlations, such as variations in symbol density arising from fixed observation lengths or modulation-dependent samples-per-symbol (SPS), are inherent to realistic signal acquisition and cannot be entirely removed without distorting the problem. However, other effects are purely artefactual. In particular, image normalization strategies and padding operations can introduce artificial intensity patterns or zero valued regions, often concentrated near the constellation origin, that may inadvertently reveal class dependent information. If not carefully controlled, a CNN may exploit these cues instead of learning the geometric structure of the constellation. In this work, such non-physical leakage sources are explicitly identified and mitigated, while unavoidable, physically meaningful correlations are preserved to maintain realism. This approach ensures that classification performance reflects genuine modulation discrimination rather than reliance on preprocessing-induced artefacts.

C. Advantages of the RGB model

The input representation strongly influences CNN-based modulation classification. In addition to grayscale histograms, an RGB color-mapped histogram is used, where bin intensities are mapped to three channels using a fixed nonlinear colormap. Although no additional physical information is introduced, this transformation creates a structured nonlinear embedding of density values into a higher-dimensional feature space, improving separability for CNN-based learning. This can be interpreted as a form of signal surface augmentation [1]. The multi-channel structure enables efficient channel-wise feature extraction while maintaining low architectural complexity. Additionally, the fixed colormap constrains dynamic range and ensures consistent scaling, improving training stability. This results in a more robust and expressive representation, particularly for lightweight CNN architectures.

VI. Results and Conclusion

Table II presents the validation accuracy obtained under five different demodulation conditions, as illustrated in Fig. 1. The proposed method exhibits a slightly longer training time due to the conversion of constellation images into three-dimensional density maps and the additional computations introduced by separable convolutional layers. However, this overhead remains limited and does not significantly affect overall training efficiency. Moreover, the results demonstrate that the breakdown of constellation-based classification is primarily driven by two critical factors: high noise levels and residual carrier frequency offset (CFO). In addition, the results highlight the strong influence of normalization strategies in classical histogram-based representations, where improper normalization can introduce information leakage and degrade model performance. In contrast, the proposed density-based representation inherently incorporates a consistent normalization mechanism, reducing sensitivity to preprocessing choices and improving robustness. In particular, under severe impairment conditions (model 4), the proposed RGB representation improves classification accuracy from 12.5% to 88.5%, demonstrating substantially improved robustness compared to conventional normalization approaches.

TABLE I: Comparison of Normalization Techniques

Normalization	**Advantages**	**Limitations**
L1	Preserves probabilistic interpretation	Sensitive to sparse histograms, poor contrast
Log	Reduces dynamic range, improves visibility	Sensitive to extreme sparsity
RGB	Preserves density, multi-channel encoding	Requires mapping selection

TABLE II: Validation accuracy (%) for different constellation representations under five test conditions

Test case	Grey L_1	Grey Log	RGB
mod2 (CFO corr., resampling, RRC)	99.6	**99.7**	99.5
mod3 (CFO corr.)	97.8	**98.8**	98.5
mod4 (CFO corr., phase shift, AWGN)	12.5	88.1	**88.5**
mod5 (phase shift, AWGN)	12.5	82.0	**83.0**
orig (CSPB.ML.2018, worst case)	12.5	44.9	**45.6**
Training time / epoch (min)	65	**60**	71

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