View Reviews

Paper ID

3220

Paper Title

Constellation Diagram Augmentation and Perturbation-Based Explainability for Automatic Modulation Classification

Track Name

Main Track

Reviewer #1

Questions

2. Relevance to IJCNN

Good

3. Technical quality

Fair

4. Novelty

Fair

5. Quality of presentation

Good

9. Comments to Authors

- conversion between complex signals and constellation diagram is really a standard technique taught in any undergraduate course in communication; authors should not take it as a part of their contributions
- the SNR bucketing is too coarse: typical communication systems require precise estimation of the background SNR before proceeding to detection/precoding; the tolerance of estimation error for general robust schemes should be about 2 or 3dB only --- a bin-width of 16dB us too much

- in benchmarking with [23], authors claims that the proposed work achieve a higher accuracy in SNR; but it does not seem to be exactly the case because [23] seeks to classify SNR precisely without the coarse binning in this work; this implies the comparison in the SNR accuracy is biased

Reviewer #2

Questions

2. Relevance to IJCNN
Good

3. Technical quality
Fair

4. Novelty
Fair

5. Quality of presentation
Very good

9. Comments to Authors
This paper proposes a method for modulation signal classification and SNR classification while introducing certain explainability validation techniques. Experimental results demonstrate that the proposed approach achieves excellent performance. However, the multi-task learning method appears to be a simple addition of two loss functions, lacking a more sophisticated strategy. Additionally, the explainability study is primarily experimental and does not contribute to algorithmic optimization.

1. The paper first converts signals into constellation diagrams before classification. However, it is unclear why this intermediate step is necessary. Would it not be possible to directly process the raw signals for classification? The authors should clarify the motivation behind this design choice.
2. Why choose to solve classification tasks instead of prediction tasks for SNR?
3. The proposed method claims to address a multi-task learning problem, yet it appears to simply sum two loss functions without additional mechanisms to balance or optimize the tasks jointly. Multi-task learning often requires strategies such as task-specific attention mechanisms, dynamic weighting, or adversarial training to prevent interference between tasks. The authors should consider incorporating such techniques to improve the effectiveness of their multi-task framework.
4. The explainability study is purely experimental and does not contribute to algorithmic improvements. Additionally, the perturbation analysis is quite limited in scope. The perturbation method only considers pixel intensity variations in the constellation

diagram, neglecting other potential influencing factors such as temporal sequence features and frequency-domain characteristics. The authors should explore more comprehensive interpretability techniques that consider the broader signal representation space.
5. The paper employs a perturbation-based explainability approach but does not compare it against other widely used interpretability techniques, such as Grad-CAM.
6. The model performs weakly on high-order modulation modes. The experimental results of the paper indicate that for high-order modulation modes such as 64-QAM and 256-QAM, the classification accuracy of the model is relatively low (64QAM: 66%, 256QAM: 79%). The article can further explore how to improve the classification accuracy of high-order modulation modes through feature enhancement, attention mechanisms, or adaptive data augmentation techniques.

Reviewer #3 | RegAC

Questions

2. Relevance to IJCNN
Good

3. Technical quality
Good

4. Novelty
Good

5. Quality of presentation
Good

9. Comments to Authors
The paper is focused into proposing a Resnet based model for classification of different types of constellation and 3 SNR levels (low, medium, high). Some explainability topics are also addressed.
The paper is well structured, clearly written and fits the conference scope.

Comments :

- On Fig.3b) and Fig.1c) seem that the learning did not converge yet.
In such curves (over the training epochs) usually the accuracy trajectories with the training data are also depicted.

- Not much about the choice of alfa and betta in eq. (5) ?

- The reported very high combined accuracy may be rather misleading taking into account the low accuracy of more complex modulations as 64QAM, 256QAM.

- The meaning of the word “augmentation” in the title and the text of the paper is not clear.

Reviewer #4

Questions

2. Relevance to IJCNN
Good

3. Technical quality
Good

4. Novelty
Fair

5. Quality of presentation
Fair

9. Comments to Authors
Overall Review

This paper presents a novel framework for Automatic Modulation Classification (AMC) that integrates multi-task learning, constellation diagram augmentation, and perturbation-based explainability. The authors aim to enhance both the performance and interpretability of deep learning models in AMC tasks, particularly in challenging environments. By transforming raw I/Q signal data into enriched constellation diagrams, the framework not only classifies modulation types but also estimates Signal-to-Noise Ratio (SNR) buckets. The use of perturbation methods provides insights into the model’s decision-making process, highlighting critical regions in the constellation diagrams. Experimental results demonstrate high accuracy and robustness across diverse modulation types, underscoring the framework’s practical implications for real-world wireless communication systems.

Strength
1. Innovative approach: Combining multi-task learning with perturbation-based interpretability to address both performance and interpretability issues is a major advancement in AMC research.

2. Actionable insights: Perturbation analysis identifies key regions in the constellation diagram, providing valuable insights that can inform further optimization and improve model credibility.

Weaknesses

1. Implementation details: The paper lacks sufficient details on the implementation of the proposed methodology, which may hinder reproducibility.

2. Experimental Evaluation: Due to the limited scope of the controlled experiments, a comprehensive assessment of the relative performance of the proposed framework cannot be achieved. It is recommended to include additional benchmark models for comparison, such as MCLDNN and CGDNet.

3. Possible issues: It has been demonstrated in previous studies that iq to constellation maps may lose some of the information leading to loss of accuracy. The resnet18 based model lacks innovation.