EMC²-Net: Joint Equalization and Modulation Classification based on Constellation Network

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Introduction

- Modulation Classification (MC) is the first step performed at the receiver side unless the transmitter explicitly indicates the modulation type. Machine learning techniques have been widely used for MC recently, but do not exploit any domain knowledge, and some works take constellation as an image.
- We propose *EMC²-Net*, a new algorithm for MC, which understands constellation as a set of 2D points (in I/Q coordinates), incurring no information loss.
- We propose a *Three-phase training strategy* to separate the roles of the equalizer and classifier, which are trained jointly under the supervision of modulation type label.
- *EMC²-Net* shows SOTA performance on classifying linear modulations with much less complexity compared to baseline methods.

Methods

System Model

- Tx: Random bits → Mod. → Norm. → Up-sampling → Pulse-shaping
- Channel: Rician/Rayleigh fading → AWGN
- Rx: Transients removal → Trimming → Norm. → Sequential data

Architecture

- Equalizer

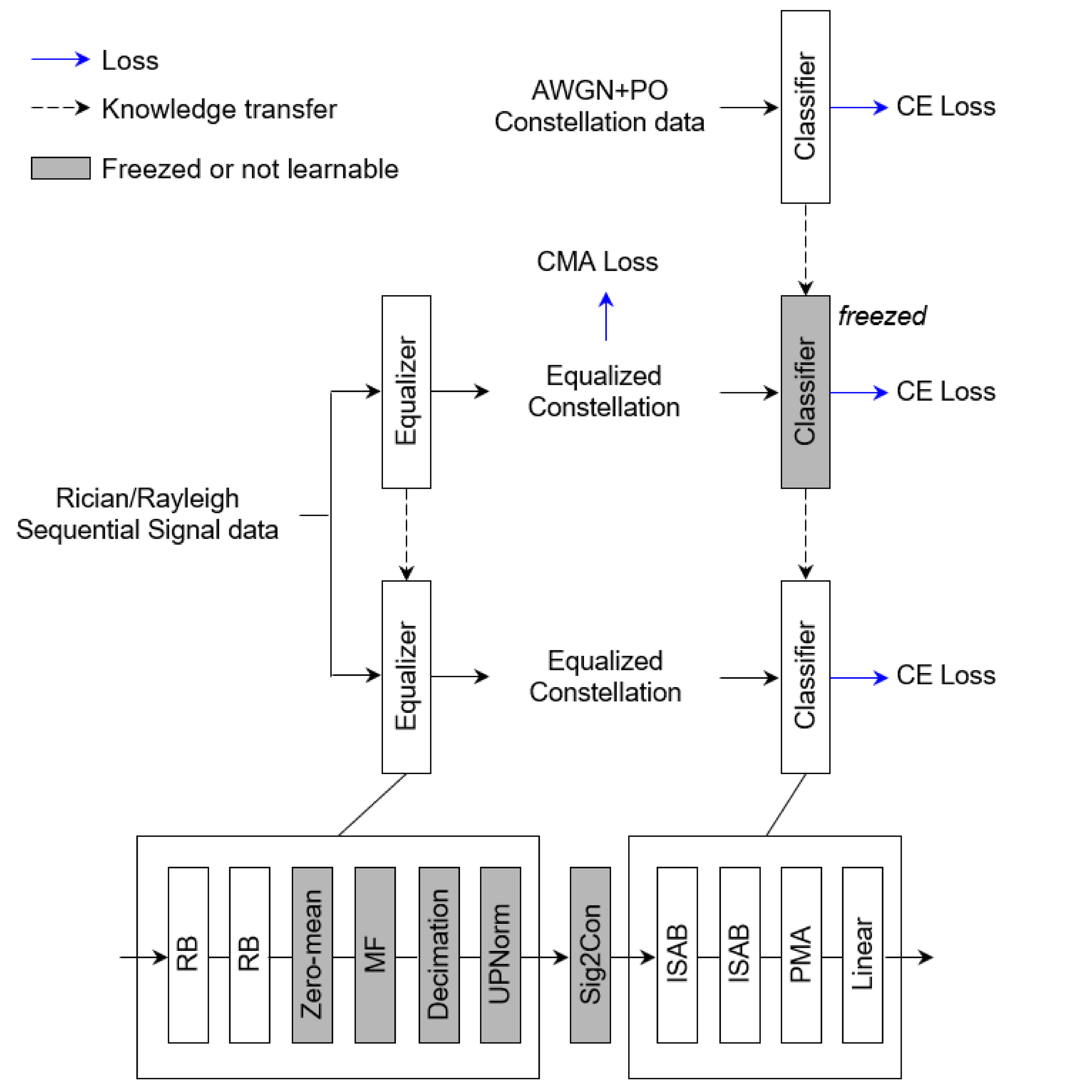
Two 1D residual blocks (RBs)
Zero-mean to eliminate DC offset
Matched filter (MF), Decimate
Normalize to unit power

- Classifier

Induced self-attention blocks (ISABs) extract features of a set of 2D points
Pooling by multi-head attention (PMA) aggregates features into lower dim.
The last linear layer gives the prob.

Training

- *Three-phase training strategy*: Classifier pretraining → Equalizer training → Equalizer-Classifier fine-tuning
- Loss functions: Phases 1 and 3 are guided by cross-entropy loss. In Phase 2, CMA loss is additionally included to enforce the Gaussianity of the equalized constellation.



Experiments

Synthetic Datasets

- 8 target linear modulations: BPSK, QPSK, 8PSK, 16QAM, 32QAM, 64QAM, 128QAM, and 256QAM
- Up-sampling factor is 8; The pulse shaping filter is an RRC filter w/ a roll-off factor of 0.35, which spans 4 symbols; The transmitter output length is 16,384
- Channel specifications are sampling rate 200 kHz; path delays [0, 9, 17] μs; average path gains [0, -2, -10] dB; maximum Doppler shift 4 Hz; K-factor 4 for Rician, 0 for Rayleigh fading. Each path consists of 18 taps with the same specifications. SNR is kept at 30 dB.
- Trimmed signal length is 8,192; Each frame contains 1,024 symbols. The total # of frames is 16K, i.e., 8 modulations with 2K frames each.
- For the AWGN+PO dataset, a random phase offset is introduced on each frame instead of fading, and SNR varies from 10 to 28 dB.

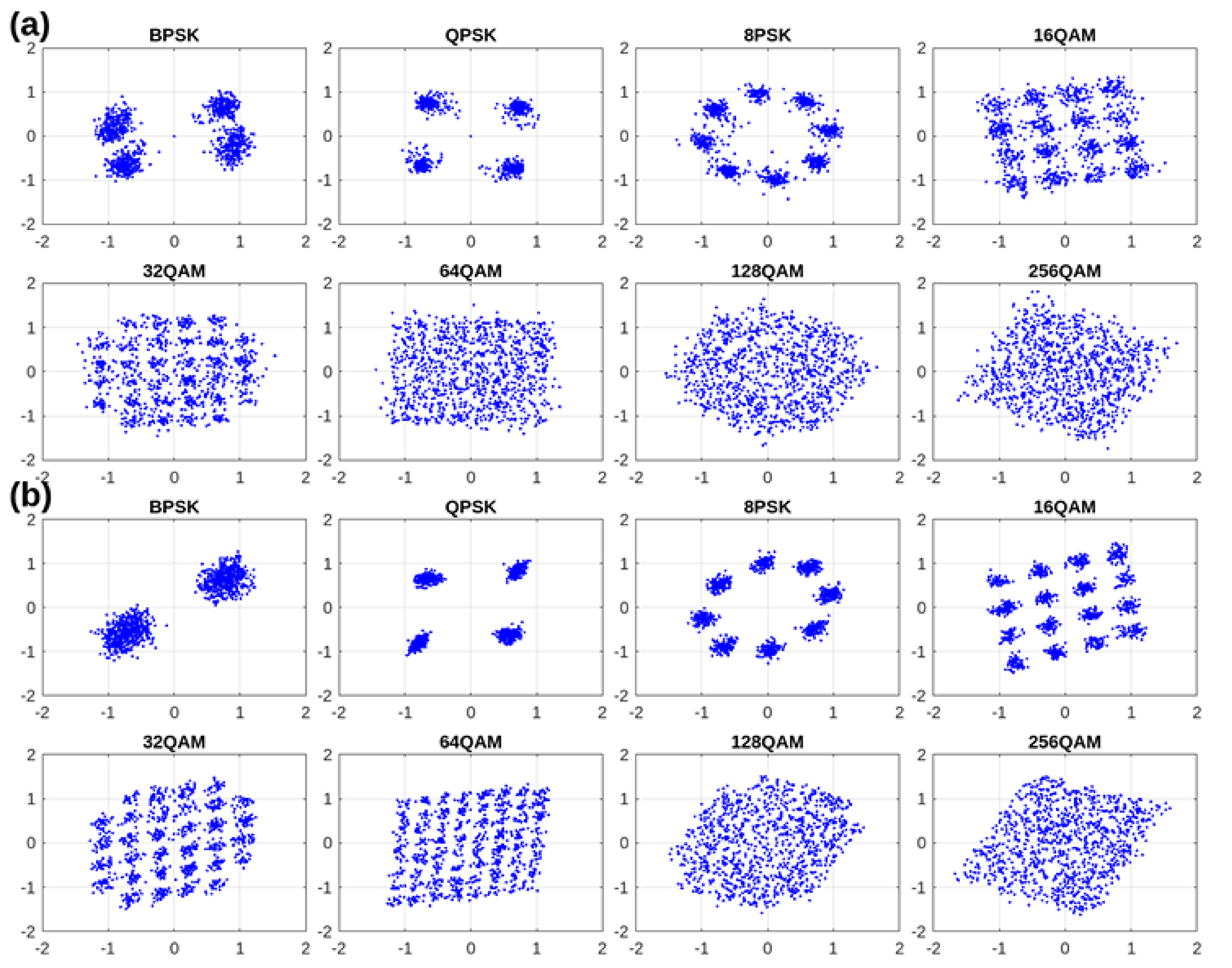
Training Details

- Adam optimizer w/ the learning rate of 10^{-3}, except that the learning rate of the classifier at Phase 3 is 2.5×10^{-4}.
- The batch size is 64 and the network is trained by 500 epochs.

Results

Method	Params (K)	Runtime (ms)	Rician (%)	Rayleigh (%)	AWGN +PO(%)
ML* [5]	N/A	N/A	68.59	62.78	**96.32**
HOC-MLP [6]	20	N/A	65.44	63.59	78.04
CNN1D [7]	167,898	0.030	53.09	49.97	60.26
ResNet1D [8]	1,175	0.209	83.72	82.91	92.17
MCNet [9]	207	0.317	**88.50**	**86.44**	92.38
ChainNet [10]	331	0.176	82.84	84.09	84.86
SCGNet [11]	441	1.704	83.00	81.34	91.42
CNN-LSTM [12]	1,150	0.310	84.62	81.22	89.86
HybridNet [13]	983	0.396	85.31	83.94	**94.22**
CNN2D* [14]	8,044	0.042	68.97	69.12	92.31
ResNet2D* [20]	602	0.252	66.78	67.09	92.74
EMC²-Net	300	0.120	**89.16**	**86.53**	**93.35**
EMC²-Net w/o P1	300	0.120	85.75	83.19	N/A
EMC²-Net w/o P2	300	0.120	**87.66**	**86.28**	N/A
EMC²-Net w/o P3	300	0.120	80.81	72.38	N/A
EMC²-Net w/ CMA	299	N/A	86.53	81.53	N/A

- *EMC²-Net* outperforms SOTA baselines on the fading datasets and gives notable result on the AWGN+PO dataset.
- *EMC²-Net* reduces the # of parameters and runtime significantly compared with baselines, even with memory-efficient CNNs.



The equalizer output of **(a) CMA** and **(b) *EMC²-Net*** of corresponding signals for each target linear modulation.