Joint Learning of Probabilistic and Geometric Shaping
Literature Review

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1 Introduction

2 Disclosure of Studies

2.1 Joint Learning of Geometric and Probabilistic Constellation Shaping [3]

2.2 Joint Learning of Probabilistic and Geometric Shaping for Coded Modulation Systems [1]

2.3 End-to-End Learning of Joint Geometric and Probabilistic Constellation Shaping [2]

This end-to-end approach proposes an auto-encoder based on the training of a cascade of neural networks. The chain consists of a mapper, channel model and demapper. Two possible demappers are suggested depending on whether symbol-metric- or bit-metric-decoding is desired.

2.3.1 Challenges

- Sampling from the symbol distribution in a differentiable manner using the Gumbel-Softmax trick is numerically unstable
- Selecting and computing the right loss function to maximize the mutual information of the end-to-end channel
- Careful integer rounding is required.

2.3.2 Loss function

The demapper shall estimate the transmitted symbol from the received. Depending on the demapping strategy, two loss functions are considered:

1. **Mutual information maximization for SMD**
   Estimates the posterior probability $Q_{\Theta,P_M,C_M}(X_n = c_m|Y_n)$ and it is trained by minimizing the Cross Entropy (CE),

$$\mathbb{X}_{\Theta,P_M,C_M}(P,Q) = -\sum_{m=1} P(Y_n|c_m)log(Q_{\Theta,P_M,C_M}(c_m|Y_n)) \tag{1}$$

$$= \mathbb{E}_{P_M,Y}[-log(Q_{\Theta,P_M,C_M}(c_m|Y_n)] \tag{2}$$

The end E2E system is trained to maximize

$$\mathbb{I}_{P_M,Y} = \mathbb{H}(P_M) - \mathbb{X}_{\Theta,P_M,C_M}(P,Q) \tag{3}$$

However, computing the derivatives of $\mathbb{I}_{P_M,Y}$ via back-propagation would make a term from the derivatives disappear since the statistics of the input symbols vary. To compensate this, this vanishing term is added to the term computed via back-propagation.

2. **Bit-wise Mutual Information maximization for BMD**
   Each c_m is mapped to a distinct bit-label using Gray bit-labelling.

References

[1] Fayal Ait Aoudia and Jakob Hoydis. Joint learning of probabilistic and geometric shaping for coded modulation systems. In *GLOBECOM 2020 - 2020 IEEE Global Communications Conference*, pages 1–6, 2020.

[2] Vahid Aref and Mathieu Chagnon. End-to-end learning of joint geometric and probabilistic constellation shaping, 2021.

[3] Maximilian Stark, Faycal Ait Aoudia, and Jakob Hoydis. Joint learning of geometric and probabilistic constellation shaping. In *2019 IEEE Globecom Workshops (GC Wkshps)*, pages 1–6, 2019.