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# Deep Learning-Based Adaptive Joint Source-Channel Coding using Hypernetworks

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## Background and Problem Formulation

Deep learning-based joint source-channel coding (DJSCC) is expected to be a key technique for the next-generation wireless networks. However, the existing DJSCC schemes still face the challenge of channel adaptability as they are typically trained under specific channel conditions. In this paper, we propose a generic framework for channel-adaptive DJSCC by utilizing hypernetworks. Then, we propose a memory-efficient hypernetwork parameterization and then develop a channel-adaptive DJSCC network, named Hyper-AJSCC.

The probabilistic formulation of JSCC problems under different scenarios:

- For **data reconstruction**

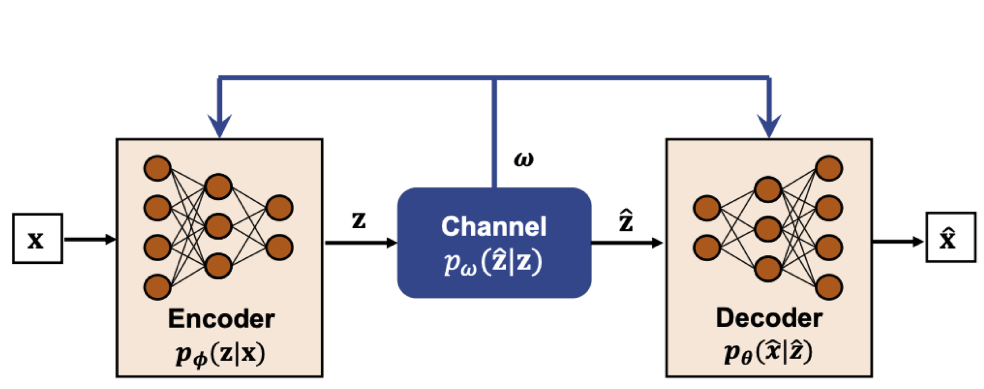
$$X \overset{\phi}{\longleftrightarrow} Z \overset{\omega}{\longleftrightarrow} \hat{Z} \overset{\theta}{\longleftrightarrow} \hat{X}$$

$$\mathcal{L}(\boldsymbol{\phi}, \boldsymbol{\theta}; \omega) = \mathbb{E}_{p(\mathbf{x})}\left[\mathbb{E}_{p_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x})p_{\omega}(\hat{\mathbf{z}}|\mathbf{z})}\left[-\log p_{\boldsymbol{\theta}}(\mathbf{x}|\hat{\mathbf{z}})\right]\right]$$

- For **cooperative inference**

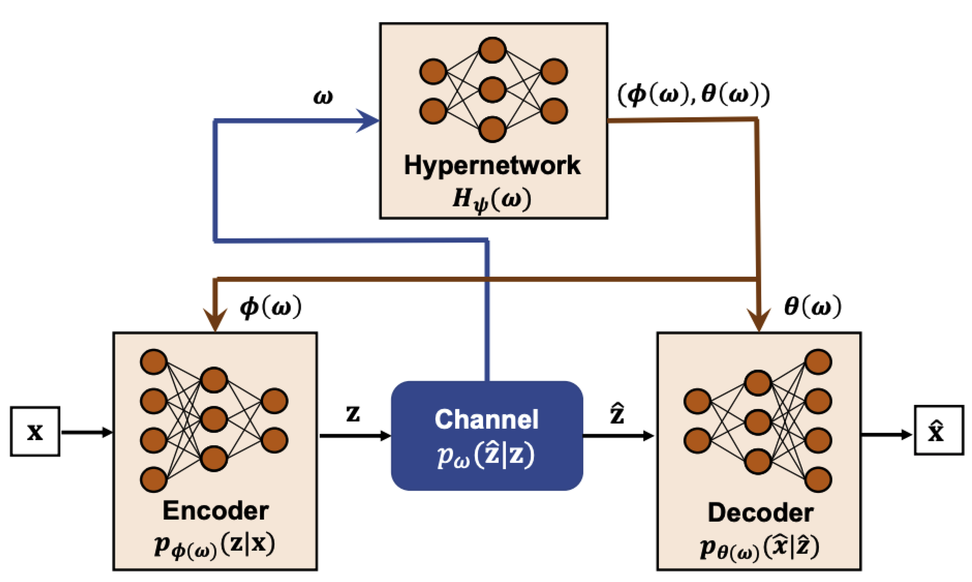
$$Y \longleftrightarrow X \overset{\phi}{\longleftrightarrow} Z \overset{\omega}{\longleftrightarrow} \hat{Z} \overset{\theta}{\longleftrightarrow} \hat{Y}$$

$$\mathcal{L}(\boldsymbol{\phi}, \boldsymbol{\theta}; \omega) = \mathbb{E}_{p(\mathbf{x},\mathbf{y})}\left[\mathbb{E}_{p_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x})p_{\omega}(\hat{\mathbf{z}}|\mathbf{z})}\left[-\log p_{\boldsymbol{\theta}}(\mathbf{y}|\hat{\mathbf{z}})\right]\right]$$



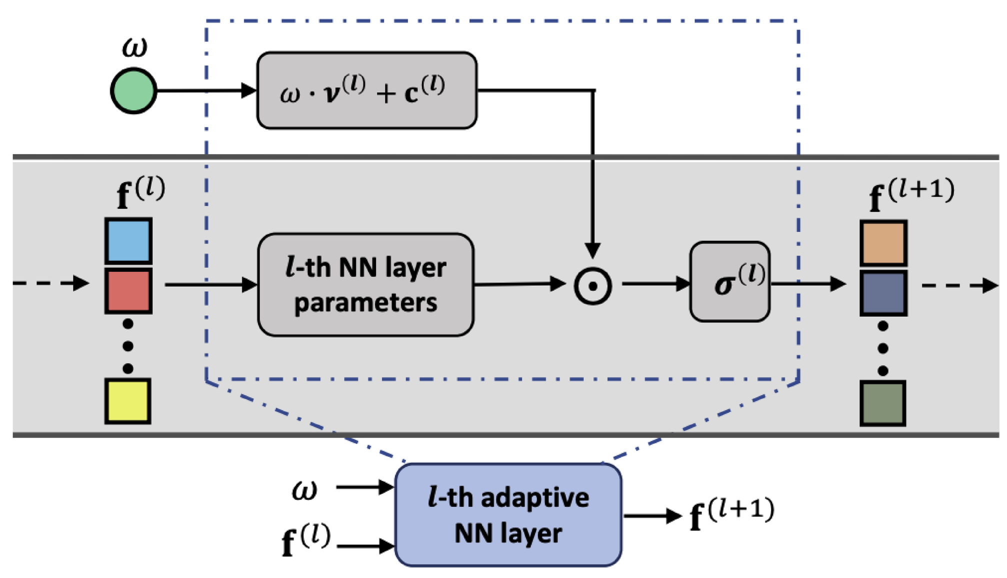

The considered system model of point-to-point communication with known channel conditions at the transmitter and receiver.

## Proposed Adaptive Deep JSCCs using Hypernetworks




**Hypernetworks for Deep JSCCs**

- Channel conditions are inputs of hypernetworks
- Hypernetworks output the parameters of the encoders and decoders
- We train the meta parameters of hypernetworks




$$\mathbf{f}^{(l+1)}(\omega) = \sigma^{(l)}(\mathbf{W}^{(l)}(\omega)\mathbf{f}^{(l)} + \mathbf{b}^{(l)}(\omega))$$
$$= \sigma^{(l)}\big(\underbrace{(\omega\cdot\boldsymbol{\nu}^{(l)} + \mathbf{c}^{(l)})}_{\text{Element-wise scaling}} \odot \underbrace{(\mathbf{W}_0^{(l)}\mathbf{f}^{(l)} + \mathbf{b}_0^{(l)})}_{\text{Basic module}}\big)$$

**Memory-efficient parameterization:** The hypernetworks can be integrated into the encoder and decoder. It can be decomposed into two main parts, *Element-wise scaling* and *Basic module*.

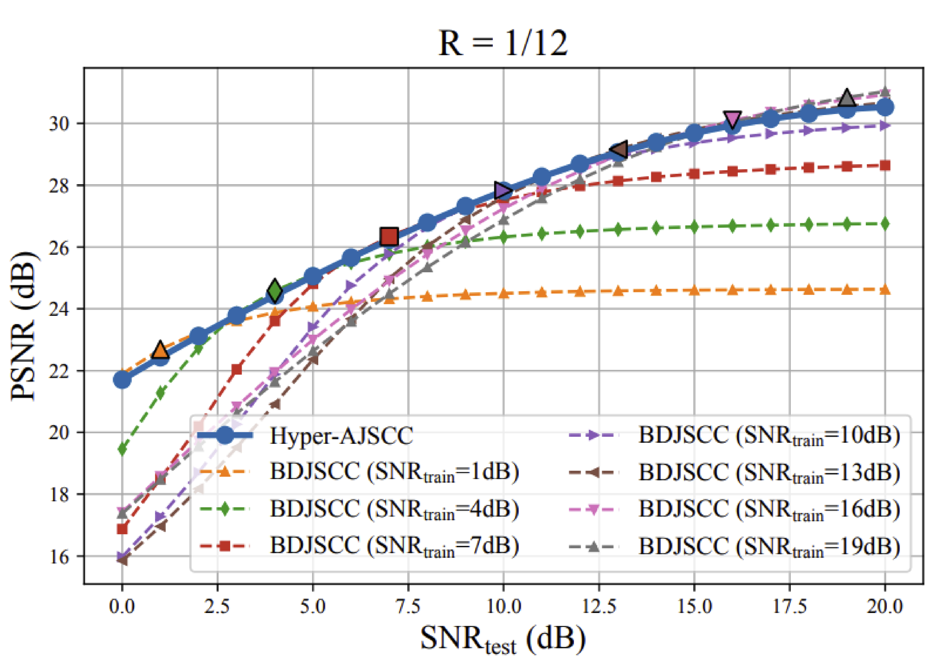
**Algorithm 1** Training Hyper-AJSCC

**Input:** $T$ (number of epochs), batch size $N$, sampling distribution for channel condition $p(\omega)$.
1: **while** epoch $t = 1$ to $T$ **do**
2: Sample a mini-batch of data samples $\{\mathbf{x}^{(i)}\}_{i=1}^{N}$
3: Sample a mini-batch of channel conditions $\{\omega^{(i)}\}_{i=1}^{N} \sim p(\omega)$
4: Generate channel models $\{p_{\omega^{(i)}}(\hat{\mathbf{z}}|\mathbf{z})\}_{i=1}^{N}$ according to $\{\omega^{(i)}\}_{i=1}^{N}$
5: **while** $i = 1$ to $N$ **do**
6: Compute $\mathbf{z}^{(i)}$ by inputting $\mathbf{x}^{(i)}$ and $\omega^{(i)}$ to the encoder
7: Estimate the received symbols $\hat{\mathbf{z}}^{(i)}$ from $p_{\omega^{(i)}}(\hat{\mathbf{z}}|\mathbf{z})$
8: Estimate the outputs by inputting $\hat{\mathbf{z}}^{(i)}$ and $\omega^{(i)}$ to the decoder
9: **end while**
10: Compute the loss $\tilde{\mathcal{H}}(\boldsymbol{\psi})$ and update the parameters $\boldsymbol{\psi}$ through backpropagation.
11: **end while**

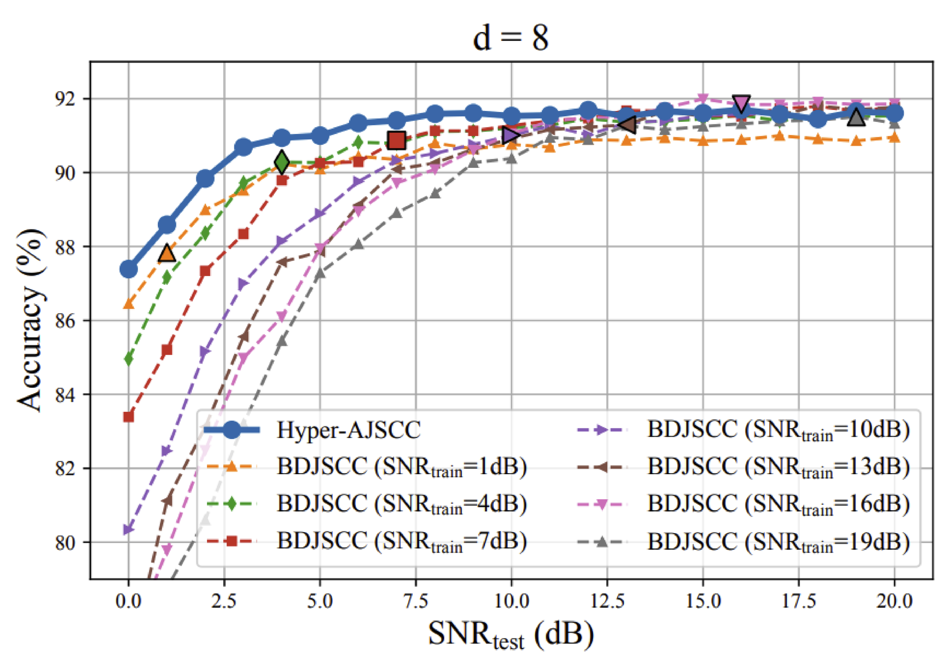
**The advantages of Hyper-AJSCC:**

- Adaptive to channel condtions
- Memory efficient
- Can be seamlessly combined with various existing DJSCC networks

## Simulation Results

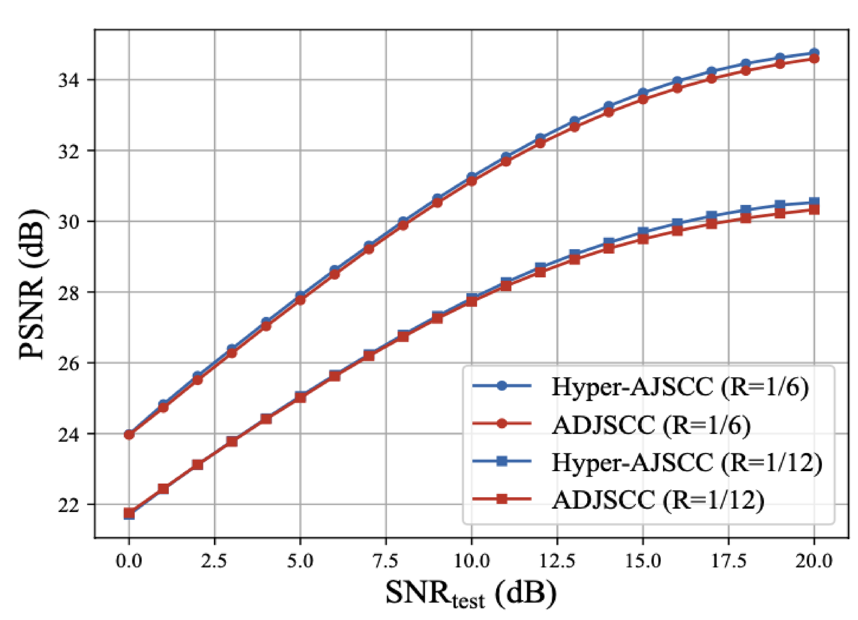



Performance of the proposed Hyper-AJSCC compared to baseline BD-JSCCs under varying training SNR with compression ratio R = 1/12. The outlined markers represent the performance of BDJSCCs when the test SNR matches their training SNR.




Performance of the proposed Hyper-AJSCC compared to baseline BDJSCCs under varying training SNR for image classification tasks. The outlined markers represent the performance of BDJSCCs when the test SNR matches their training SNR.

| Method | # parameters | Storage |
|---|---|---|
| ADJSCC | 67840 | 265 KB |
| Hyper-AJSCC | **4118** | **16 KB** |




Memory overhead and performance of the proposed Hyper-AJSCC compared to ADJSCC with different compression ratios

### Related Publications

- **S. Xie**, H. He, H. Li, S. Song, J. Zhang, Y. J. A. Zhang, and K. B. Letaief, "Deep Learning-Based Adaptive Joint Source-Channel Coding using Hypernetworks," in **2024 IEEE International Mediterranean Conference on Communications and Networking (MeditCom),** Madrid, Spain, 2024

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