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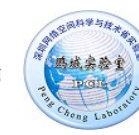
Universal Efficient Variable-rate Neural Image Compression

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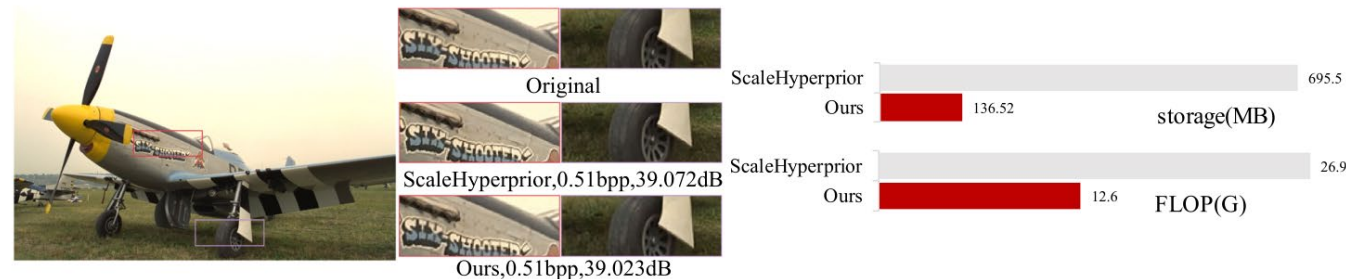


1. Introduction



- **Image compression** is a fundamental technology in signal processing and computer vision.
- In recent years, **many learning-based image compression** methods have achieved **state-of-the-art** performance comparing to traditional image codecs.
- However, there are still some challenges for its **practical deployment**:
 - **Bit-rate and reconstruction quality are fixed** for a single trained model with a predefined trade-off factor.
 - **Computational cost** in learning-based compression models is relatively high due to their complex network architectures.

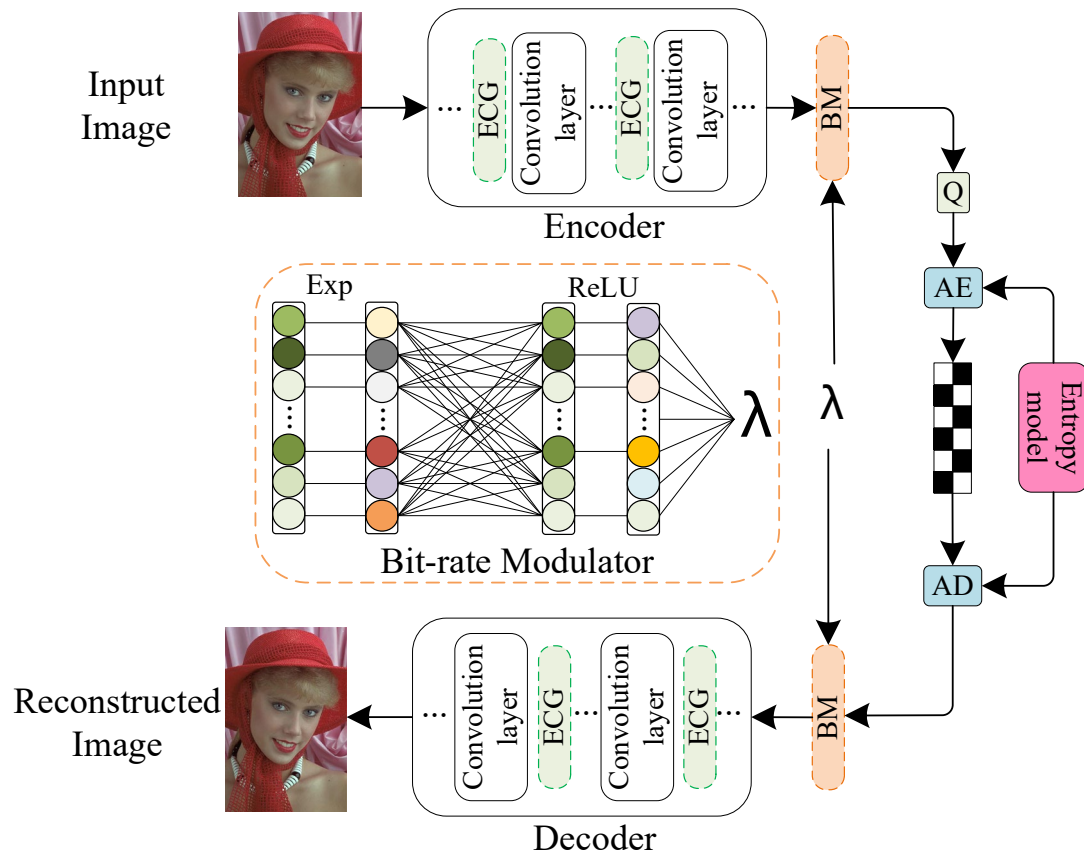
To deal with such situation and corresponding challenges of learning-based image compression, this paper proposes a **universal variable-rate efficient** method for neural image compression.



2. Method



Overall Framework



Two novel modules are purposed—**Energy-based channel gating module**(ECG) and **Bit-rate modulator**(BM).

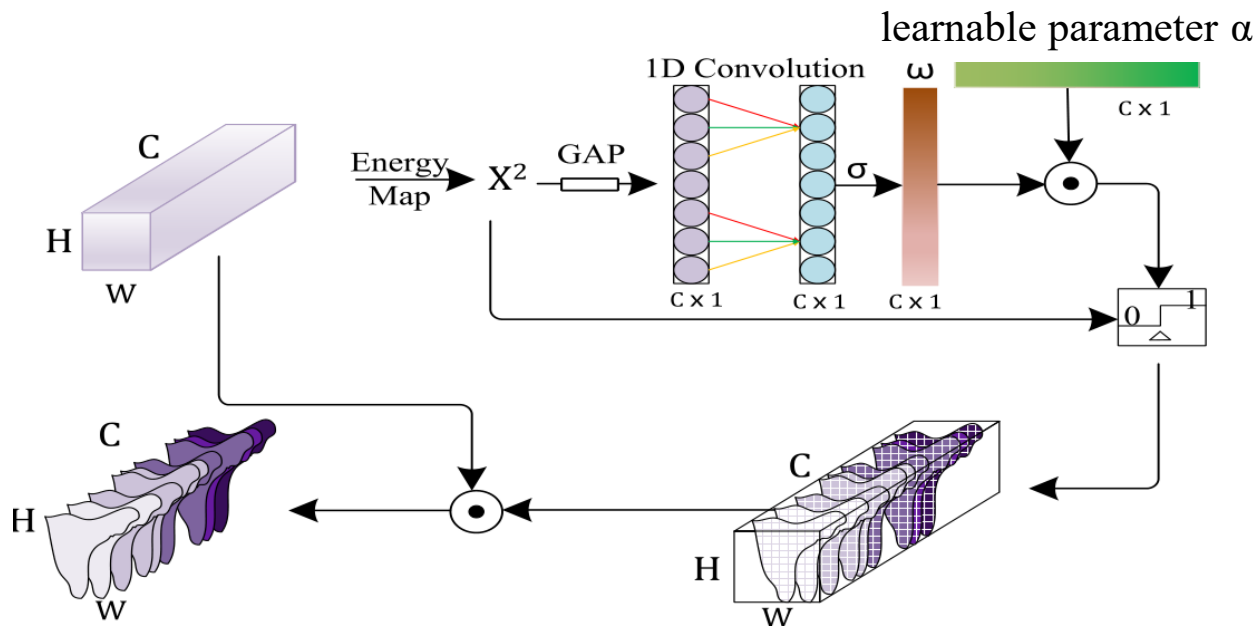
- **ECG** embedded before each convolution layers to get sparse convolutional inputs.
- **BM** inserted outside entropy coding process to modulate the latent representation.
- **Comprehensive** optimization formulation:

$$\operatorname{argmin}_{\theta, \phi, \xi, \lambda} \sum_{\lambda \in \Lambda} [R + \lambda D + \gamma \sum_{i=1}^n (\alpha_n - \alpha_t)^2]$$

2. Method

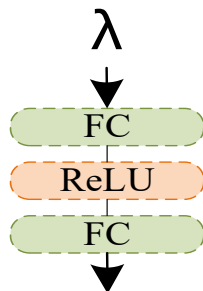


Energy-based channel gating



- Inputs of **different intensities** cause different influence on the results \rightarrow learnable dynamic feature map pruning with **channel-wise threshold**.
- Global pooling for **intra-channel** information
- 1D-convolution for **inter-channel** information

Bit-rate modulator

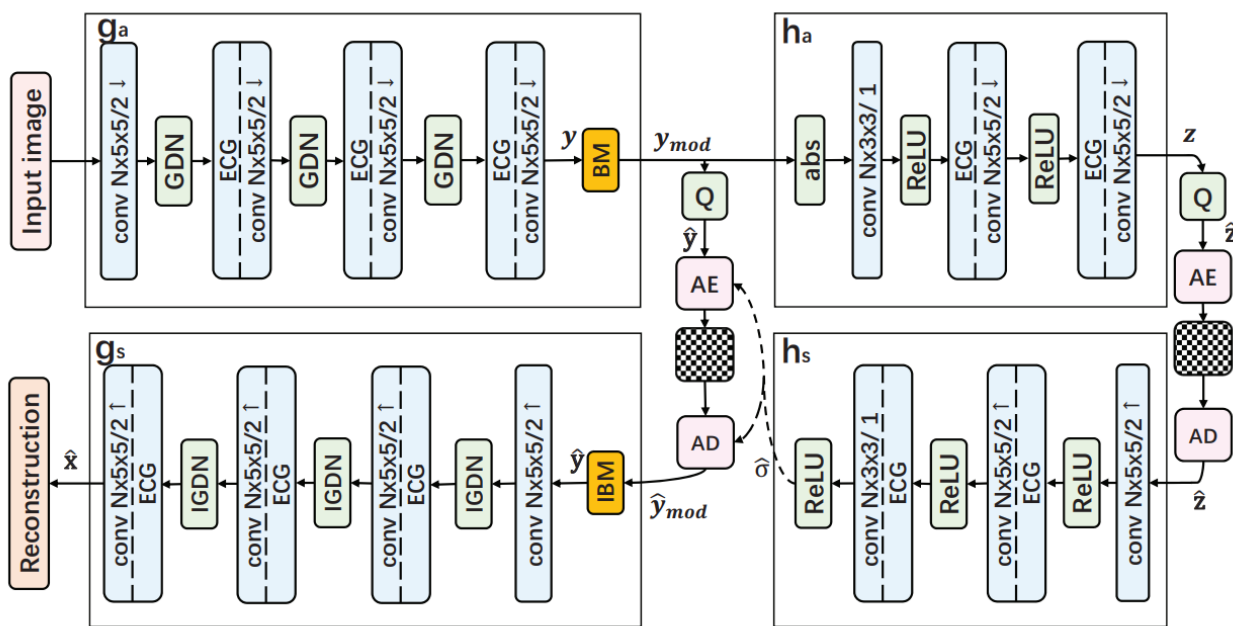


- Mapping a trade-off factor λ into a vector
- Simple: Two full-connected layer
- Effective: Plug-in manner

3. Experiments



We use ScaleHyperprior model as an example to show the implementation details and optimization strategies of our method.



Distortion: mean square error measured on the test set

$$D(x, \hat{x}; \theta, \phi, \xi, \lambda) = \mathbb{E}_{x \sim p_x} [\|x - \hat{x}\|^2]$$

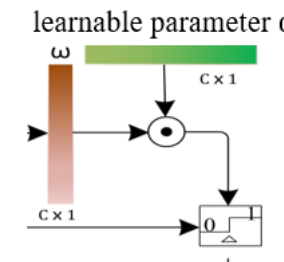
Rate: cross entropy of the estimated distribution of y and the its actual distribution

$$R(\hat{y}; \theta, \phi, \xi, \lambda) = \mathbb{E}_{\hat{y} \sim p_y} \{ \log_2 q_y [Q(y \odot bm(\lambda))] \}$$

In ECG, the **learnable adjustment vector α** affect the final gating threshold th , **larger** the α is, **higher** the final threshold on each channels will be, and the output feature map of ECG will be **sparser**.

Final optimization formulation:

$$\operatorname{argmin}_{\theta, \phi, \xi, \lambda} \sum_{\lambda \in \Lambda} [R + \lambda D + \gamma \sum_{i=1}^n (\alpha_n - \alpha_t)^2]$$

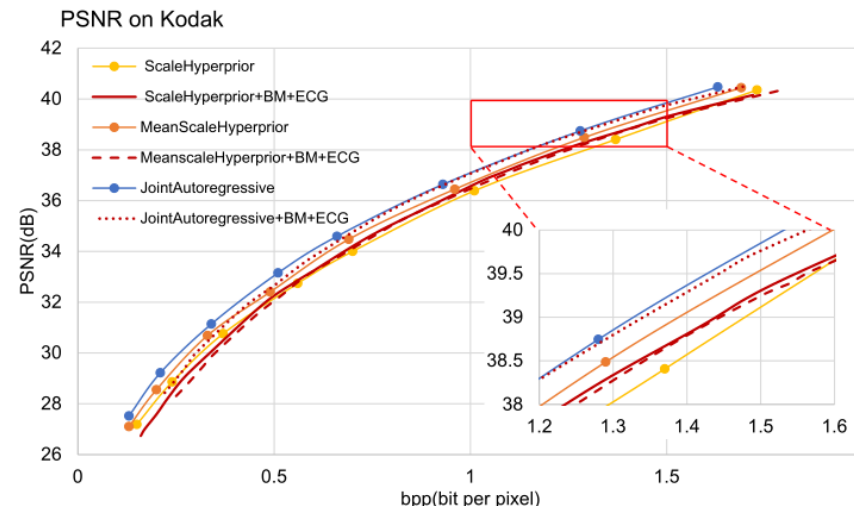
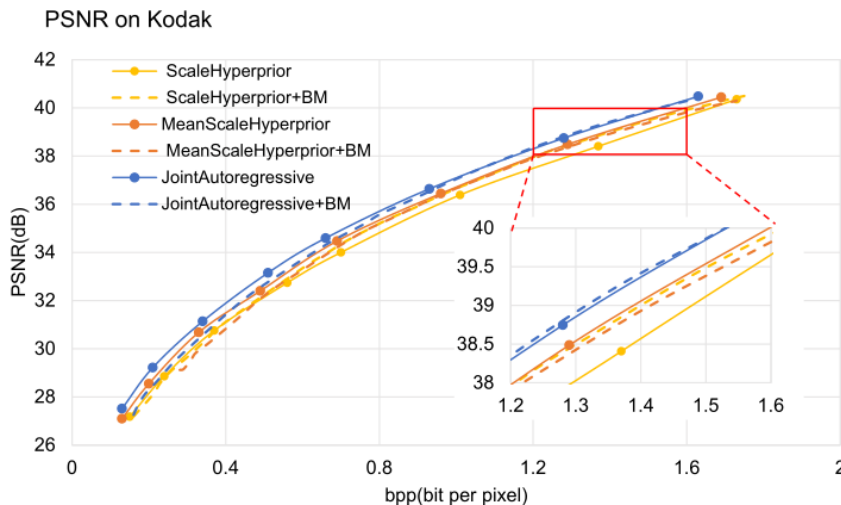


3. Experiments



Model	Performance	Quality							
		1	2	3	4	5	6	7	8
ScaleHyperprior	PSNR drop(%)	0	0.346	0.228	0.269	0.336	0	0	0.216
	FLOP reduction	2.54 ×	2.86 ×	2.60 ×	2.54 ×	2.54 ×	2.07 ×	2.14 ×	2.03 ×
MeanscaleHyperprior	PSNR drop(%)	0.39	0.22	0.77	0.69	0.37	0.61	0.71	0.78
	FLOP reduction	2.34 ×	2.50 ×	2.56 ×	2.68 ×	2.33 ×	2.12 ×	2.12 ×	2.24 ×
JointAutoregressive	PSNR drop(%)	0.207	0.335	0.437	0.807	0.465	0.150	0.354	0.553
	FLOP reduction	2.43 ×	2.67 ×	2.48 ×	2.23 ×	2.29 ×	2.02 ×	2.06 ×	2.02 ×

For model with ECG: We can see that the FLOP reduction of more than 2× can be achieved in three neural image compression models with very slight PSNR degradation around 0.5% and no more than 1%



For efficient models: Comparable performance to original models. Sparsity around 0.5 in convolution operations. Storage saving of 80.42%, 82.04% and 83.07% respectively.

For models with BM: continuous rate flexibility can be achieved.

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Thank you!

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