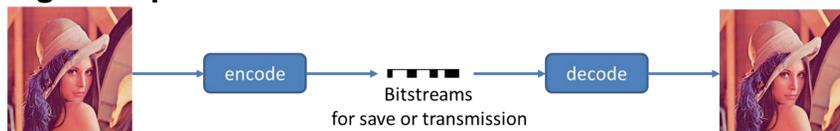


Introduction

Image compression:



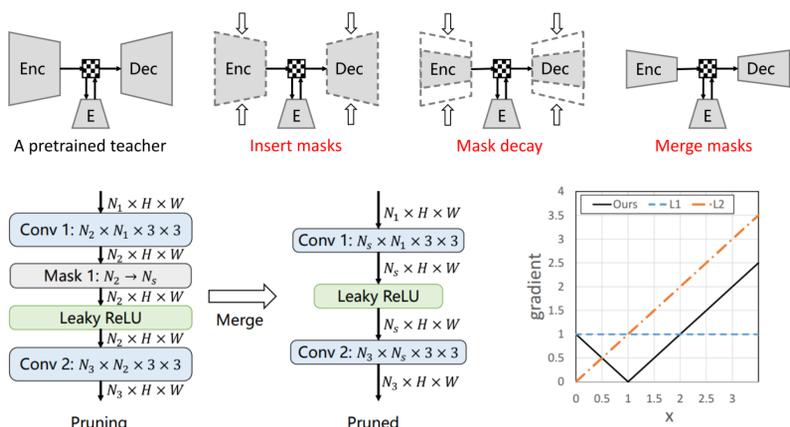
Main problems of neural image compression:

- The **large complexity**
- The **inefficient rate-control**

Our contributions:

- We propose an **Efficient Variable-bit-rate Codec (EVC)** for image compression. It enjoys only one model for different RD trade-offs. Our model is able to run at 30 FPS for the 768 × 512 inputs, while is on-par with other SOTA models for the RD performance. Our small model even achieves 30 FPS for the 1920 × 1080 inputs.
- We propose **mask decay**, an effective method to improve the student image compression model with the help of the teacher. A **novel sparsity regularization loss** is also introduced, which alleviates the shortcomings of L_p regularization. Thanks to mask decay, our medium and small models are significantly improved by 50% and 30%, respectively.
- We enable the encoding scalability for neural image compression. With **residual representation learning** and mask decay, our scalable encoder significantly narrows the performance gap from the teacher and achieves a superior RD performance than previous SlimCAE.

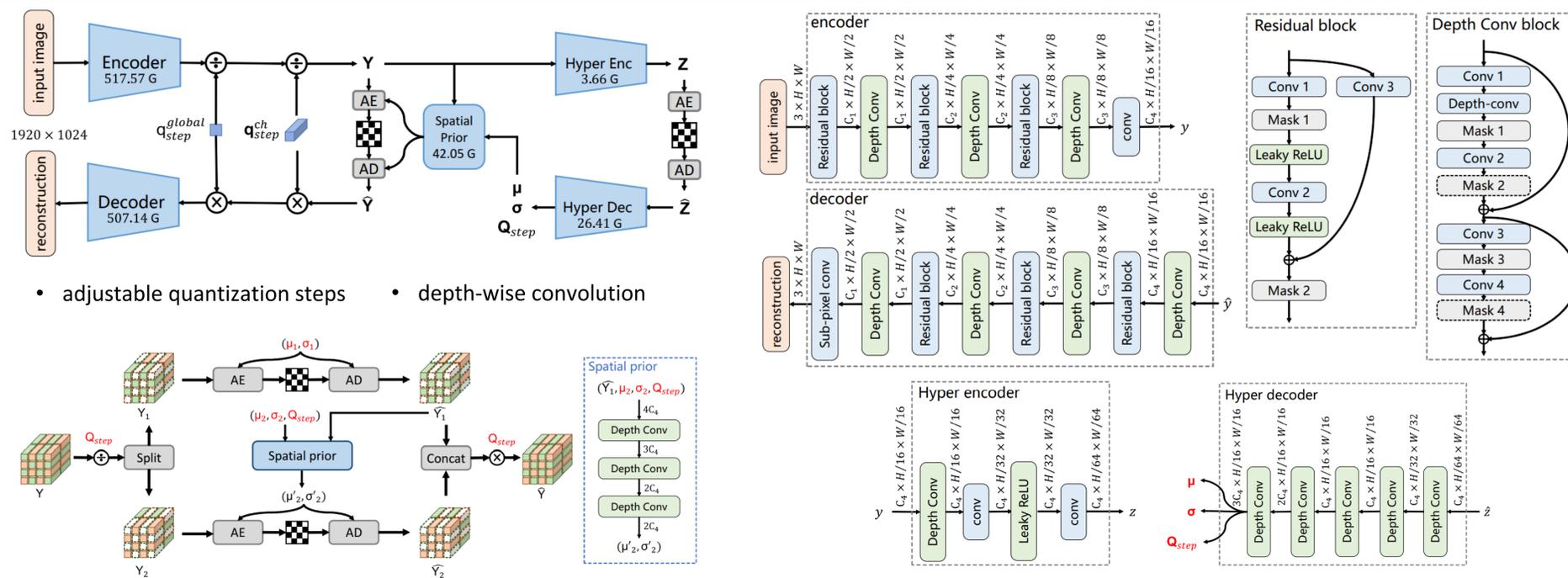
Mask Decay



- The gradient of L2 vanishes when x approaches zero
- The gradient of L1 is a constant without considering its own magnitude

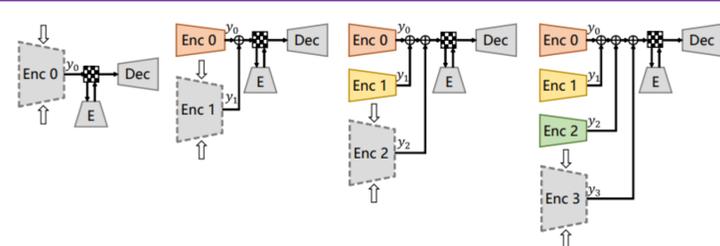
• Ours: $\frac{\partial \mathcal{L}_{sparse}(x)}{\partial x} = |x - 1|$, $\mathcal{L}_{sparse}(x) = \begin{cases} -\frac{1}{2}x^2 + x, & \text{if } 0 \leq x \leq 1, \\ \frac{1}{2}x^2 - x + 1, & \text{if } x > 1. \end{cases}$

The EVC Framework

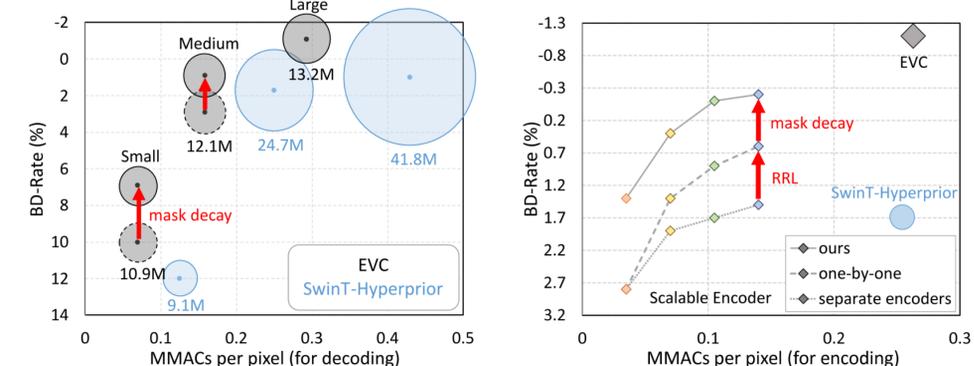


- adjustable quantization steps
- depth-wise convolution

Residual Representation Learning (RRL)



Experimental Results



Latency

Resolution	GPU	Type	Latency					
			Entroformer	STF Transformer	CNN	Large	EVC Medium Small	
768 × 512	2080Ti	encoding	OM	176.3	158.5	63.0	44.7	28.4
		decoding	OM	202.3	210.2	41.1	32.4	24.4
1920 × 1080	A100	encoding	816.8	115.9	96.4	21.1	19.8	17.7
		decoding	4361.9	143.2	118.0	19.1	17.1	15.6

