CFSNet: Toward a Controllable Feature Space for Image Restoration

Wei Wang — Tsinghua University
Ruiming Guo — Chinese University of Hong Kong
Yapeng Tian — University of Rochester
Wenming Yang — Tsinghua University

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INTRODUCTION

➢Motivation

- Most deep learning methods are often goal-specific and lack flexibility.
- Image quality assessment from personal opinion is relatively subjective, and low reconstruction distortion is not always consistent with high visual quality.
- In many practical applications, it is often challenging to obtain user's preference and the real degradation level of the corrupted images.

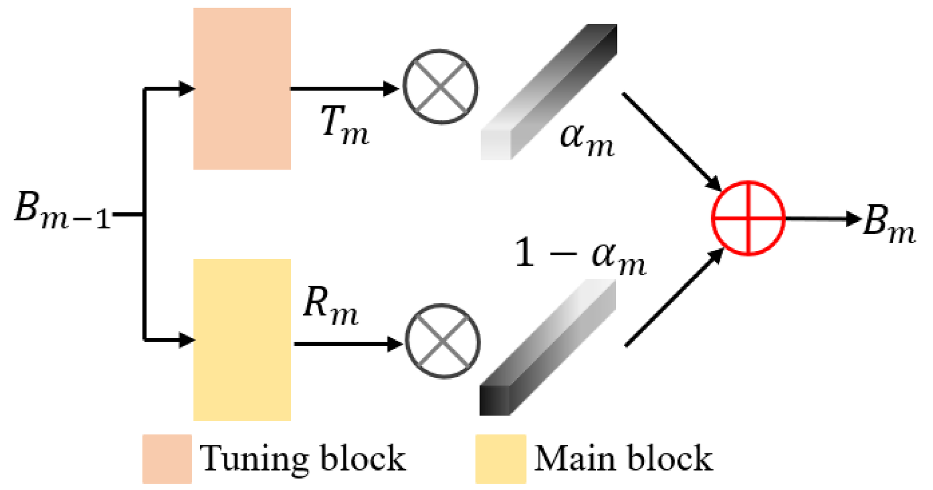
➢Contribution

- We propose a novel framework equipped with controllability for human perception-oriented interactive image restoration.
- We design a coupling module and an adaptive learning strategy of coupling coefficients to implement interactive image restoration.

PROPOSED METHOD

➢Network Architecture

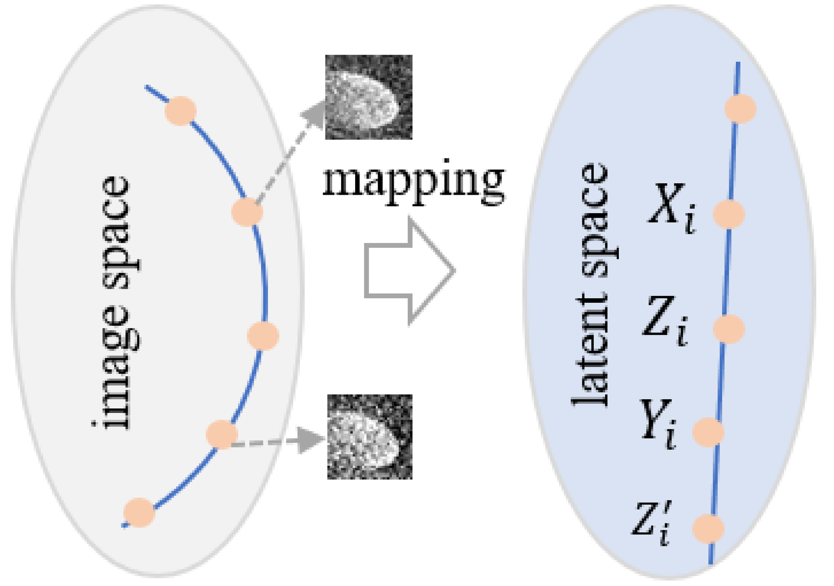
- **Coupling module**: we realize the interactive control of the reconstruction result by tuning the features of each unit module, called coupling module. Each coupling module consists of a main block and a tuning block. The parameters of two blocks are obtained under two endpoint optimization objectives. Besides, as a key to achieving fine feature control, we assign the highdegree-of-freedom coupling coefficients adaptively learned from a control scalar to each coupling module.

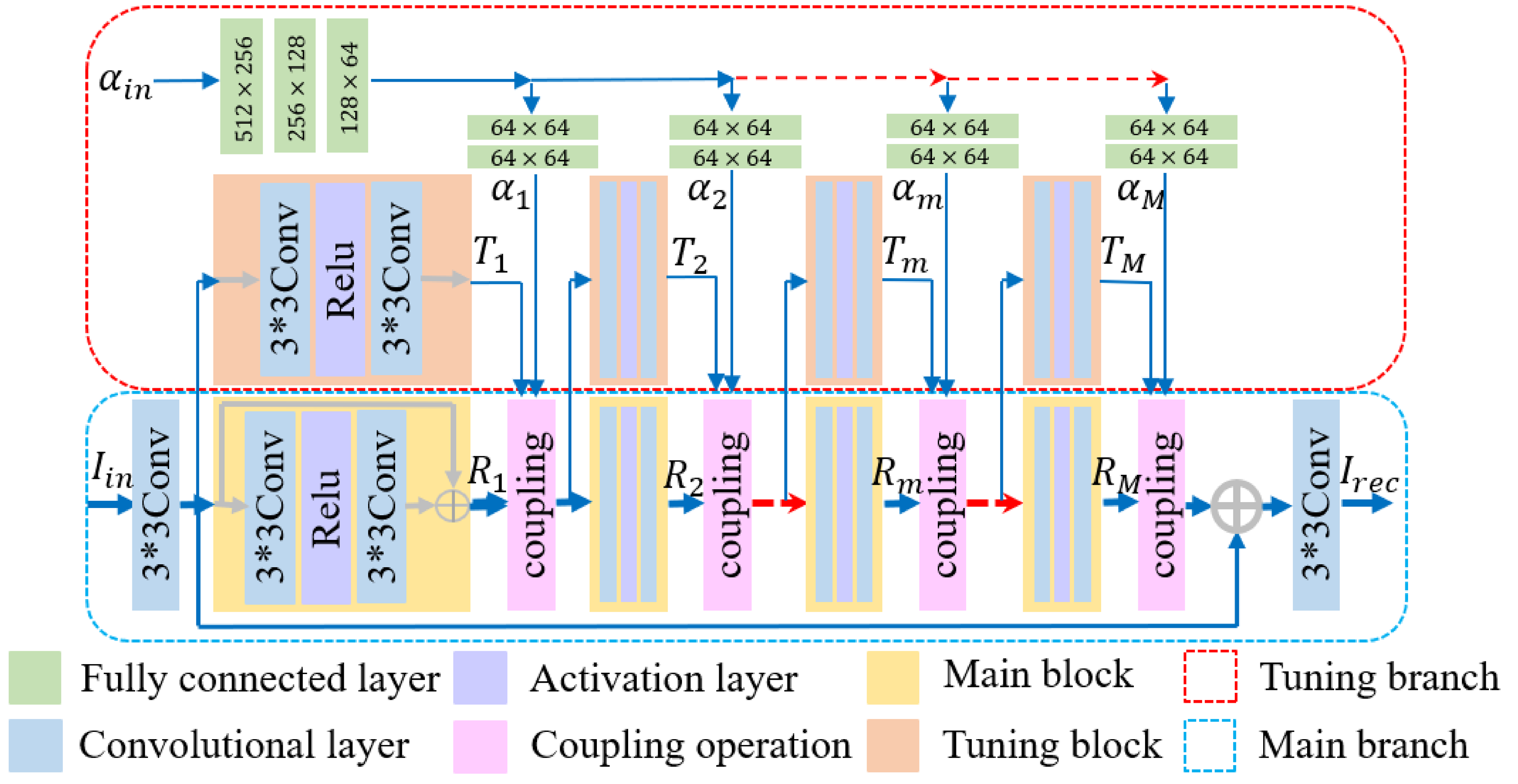


$$B_m = (1-\alpha_m)R_m + \alpha_m T_m = R_m + \alpha_m(T_m - R_m)$$
$$= R_m + F_{alpha}(\alpha_{in})(T_m - R_m)$$

- **Rationality:** Data manifold can be flattened by neural network mapping and the mapped manifold can be more reasonably approximated as Euclidean space. The unknown point Z_i can be represented as an affine combination of two known endpoints X_i and Y_i.

Coupling module



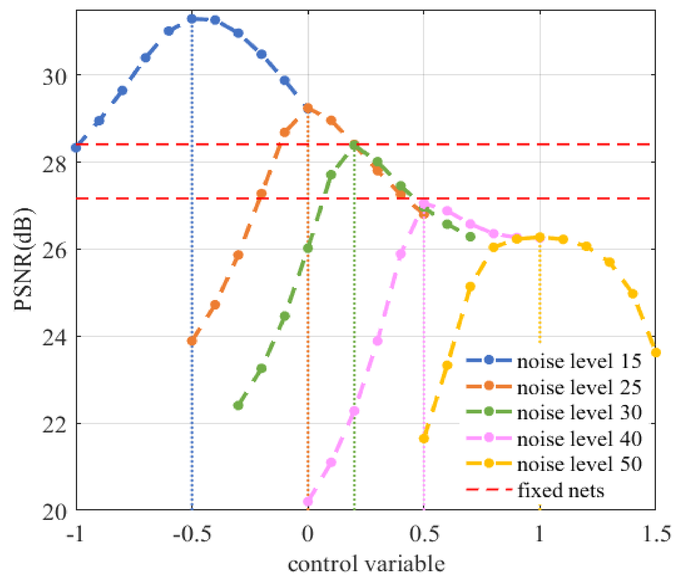


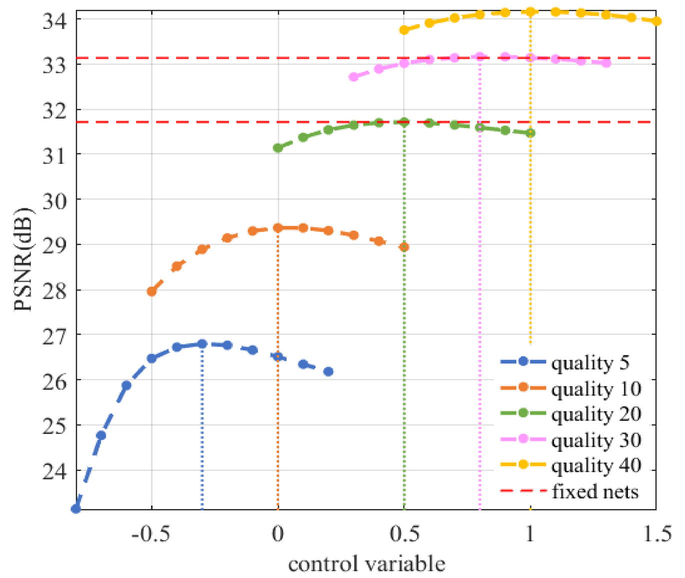
The framework of our proposed controllable feature space network (CFSNet)

- **Training:**
  - **Step 1:** Set the control variable α_{in} as 0. Train the main branch with the loss function $L_1(I_{rec}, I_g; \theta_{main})$, where I_g is the corresponding ground truth image.
  - **Step 2:** Set the control variable α_{in} as 1. Map the control variable α_{in} to different coupling coefficients $\{\alpha_m\}$, fix parameters of the main branch and train the tuning branch with another loss function $L_2(I_{rec}, I_g; \theta_{tun}, \theta_\alpha)$.

EXPERIMENTAL RESULTS

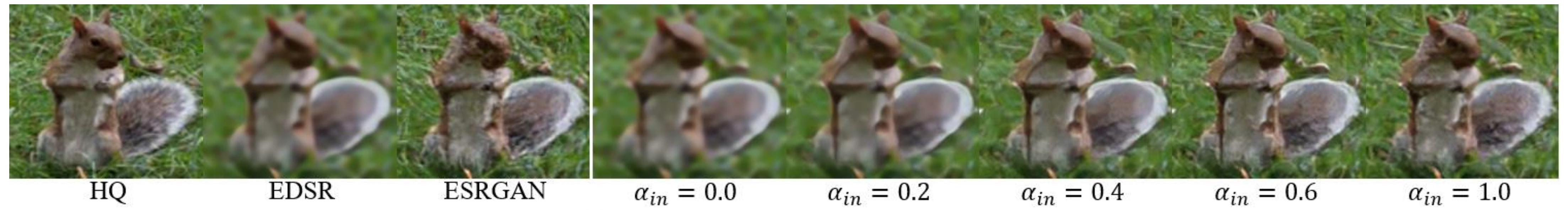
➢Model Analyses



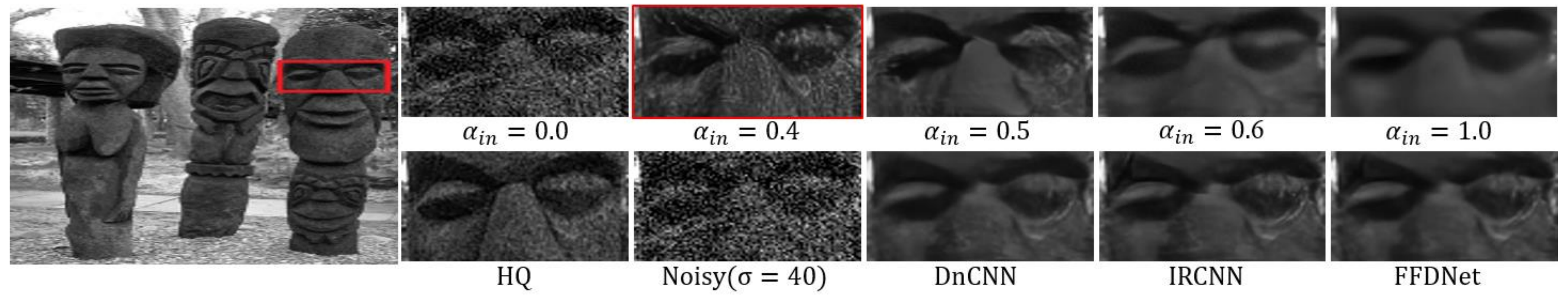


(1) PSNR-α_{in} curve of image denoising task on the BSD68 (gray) dataset.
(2) PSNR-α_{in} curve of JPEG image deblocking task on the LIVE1 dataset.

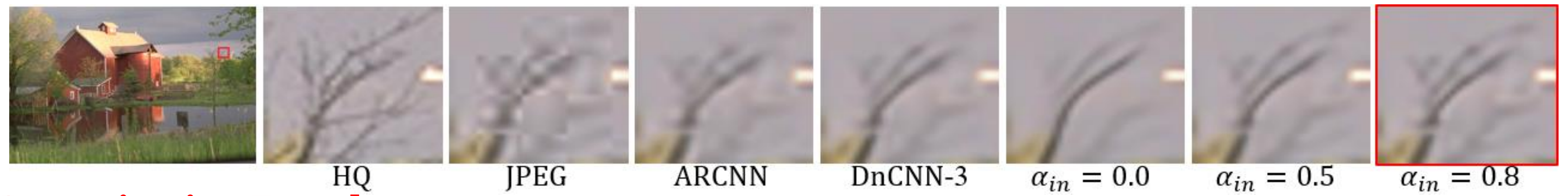
➢Image Super-resolution: The perception-distortion trade-off of image super-resolution



➢Image Denoising: The trade-off between noise reduction and detail preservation.



➢JPEG Image Deblocking: JPEG image artifacts removal results of "house" (LIVE1) with unknown quality factor 20.



➢Quantitative Results

Table 1. Benchmark image denoising results. The average PSNR(dB) for various noise levels on (gray) BSD68. *denotes unseen noise levels for our CFSNet in the training stage.

methods	$\sigma = 15^*$	$\sigma = 25$	$\sigma = 30^*$	$\sigma = 50$
BM3D	31.08	28.57	27.76	25.62
TNRD	31.42	28.92	27.66	25.97
DnCNN-B	31.61	29.16	28.36	26.23
IRCNN	31.63	29.15	28.26	26.19
FFDNet	31.63	29.19	28.39	26.29
CFSNet	31.29	29.24	28.39	26.28

Table 2. Benchmark JPEG deblocking results. The average PSNR(dB) on the LIVE1 dataset. * denotes unseen quality factors for our CFSNet in the training stage.

methods	$q = 10$	$q = 20^*$	$q = 30^*$	$q = 40$
JPEG	27.77	30.07	31.41	32.35
SA-DCT	28.65	30.81	32.08	32.99
ARCNN	28.98	31.29	32.69	33.63
TNRD	29.15	31.46	32.84	N/A
DnCNN-3	29.19	31.59	32.98	33.96
CFSNet	29.36	31.71	33.16	34.16