High-dimensional Embedding Denoising Autoencoding Prior for Color Image Restoration

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Joint work with
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Outline

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2. Image deblurring

Conclusions: An enhanced DAEP for color IR !

Part I – Background:

Image Restoration (IR) Model

Denoising Autoencoding (DAE)

Background 1: Image restoration (IR) model

$$\hat{u} = \arg\min_{u} \| Hu - f \|^2 + \lambda \varphi(u)$$

Regularization term:

Exploits characteristics of a natural image

Data-fidelity term:

Ensures that the solution conforms to the degradation process

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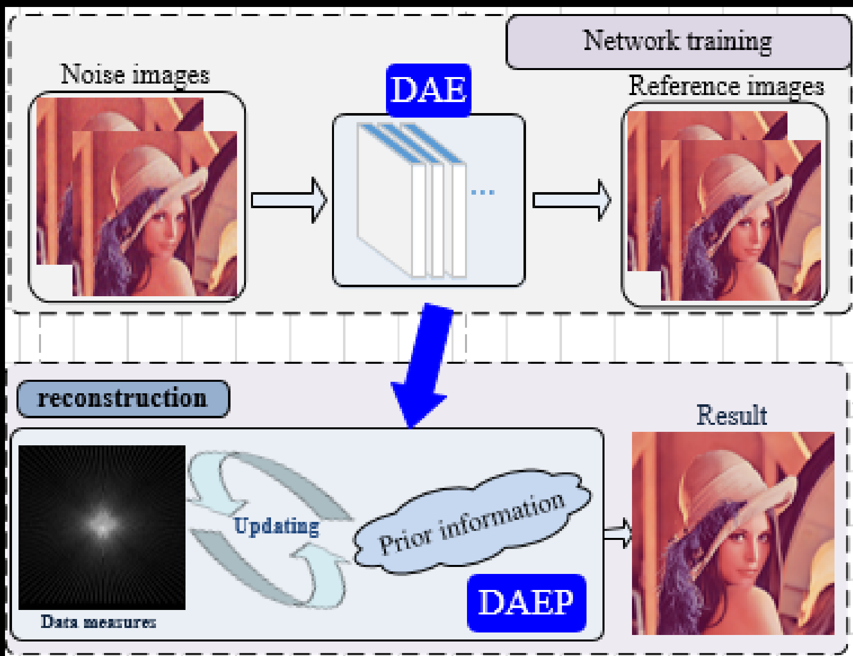
Background 2: Denoising autoencoding (DAE)



Unsupervised learning !!!

DAEP

$$\left\| A_{\sigma_\eta}(u) - u \right\|_2^2$$

The autoencoder error $A_{\sigma_\eta}(u) - u$ is proportional to the gradient of the log likelihood of the smoothed density:

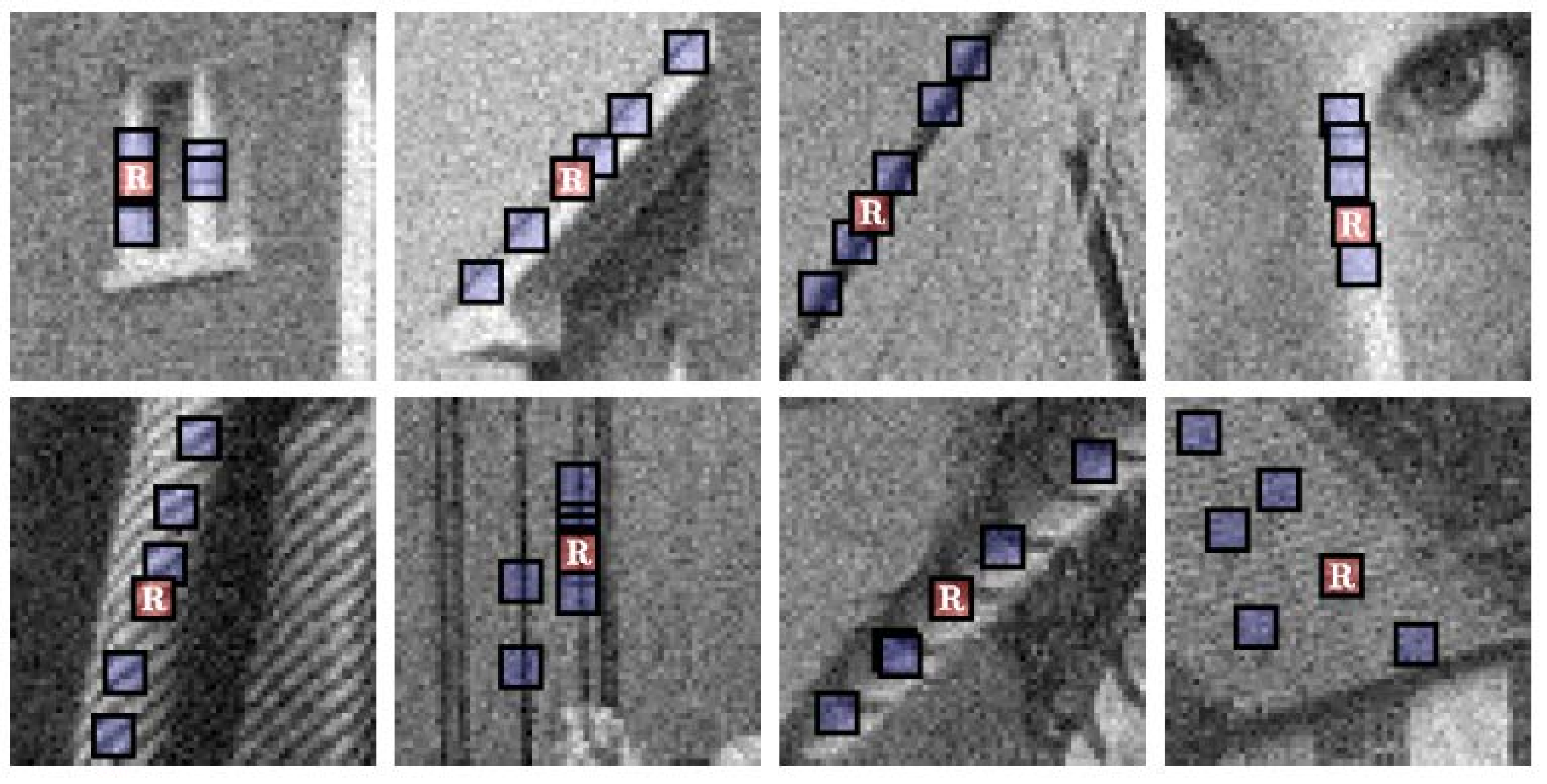
$$A_{\sigma_\eta}(u) - u = \sigma_\eta^2 \nabla \log[g_{\sigma_\eta} * q](u)$$

where the data distribution is $Probability(u) = \int q(u+\eta) d\eta$

Refs: S.A. Bigdeli and M. Zwicker, “Image restoration using autoen-coding priors,” arXiv preprint arXiv: 1703.09964, 2017.

Part II – Proposed M^2DAEP

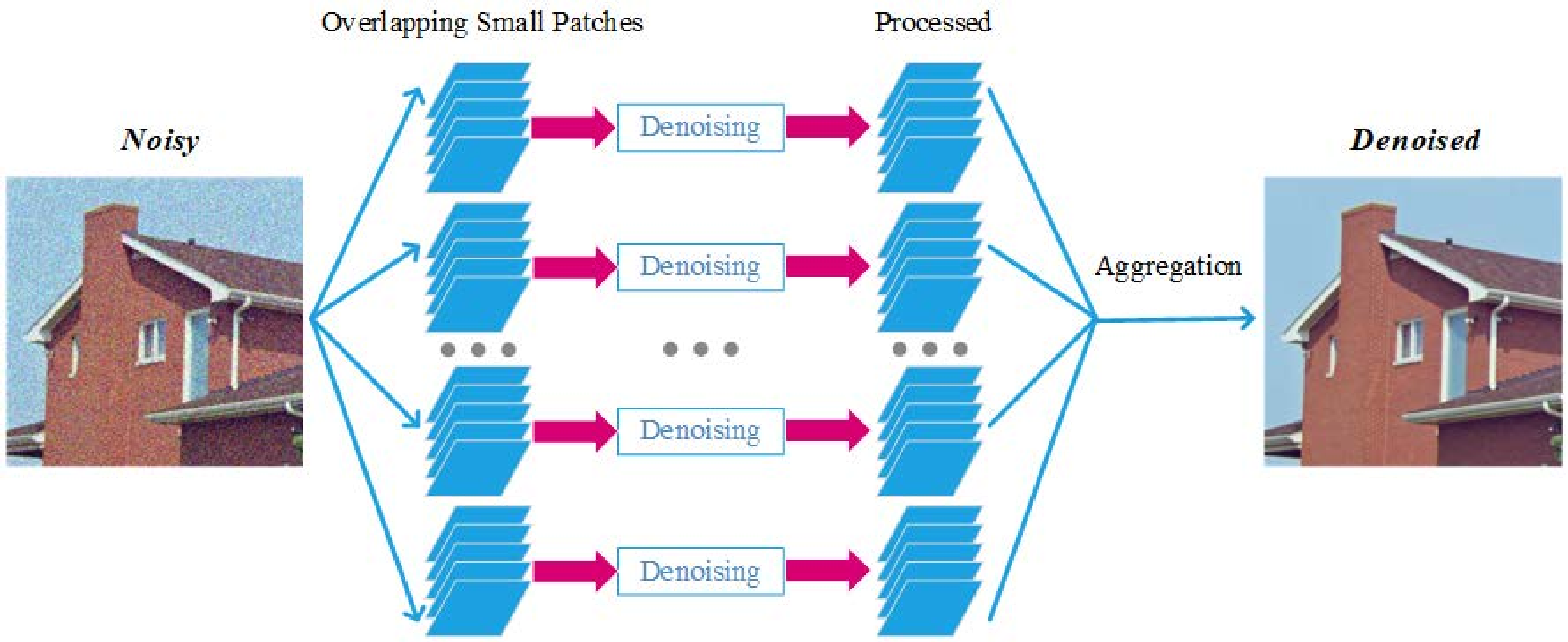
Motivation 1: Patch-based methodology (image similarity)



Refs: Buades et al. 2005; Elad et al. 2006; Dabov et al. 2006; Milanfar et al., 2007; Zhang et al., 2010; Dong et al., 2012.

Motivation 2: Image patch aggregation strategy

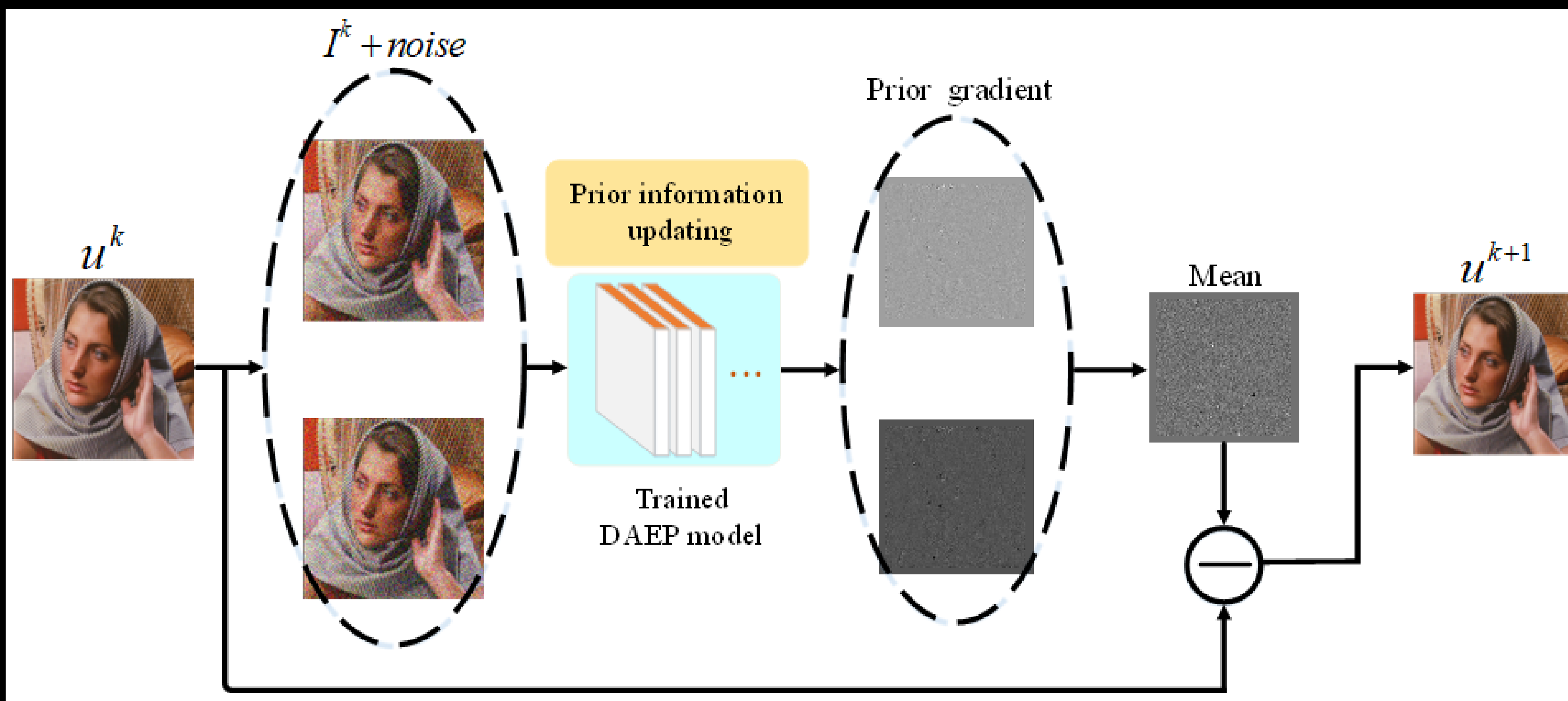
The patch matching procedure enables multi-patches with similar structural patterns to be found and grouped.



Refs: Mairal et al. 2007; Mousavi et al. 2017; Dabov et al. 2007; Danielyan et al., 2012; Zoran et al., 2011; Dong et al., 2015.

Idea: Multi-model implementation

Inspired by image patch similarity and aggregation strategy, we adopt a multi-models and 6-dimensional version of DAEP for color IR tasks.



Convolution operator in multi-channel image features at iterative procedure.

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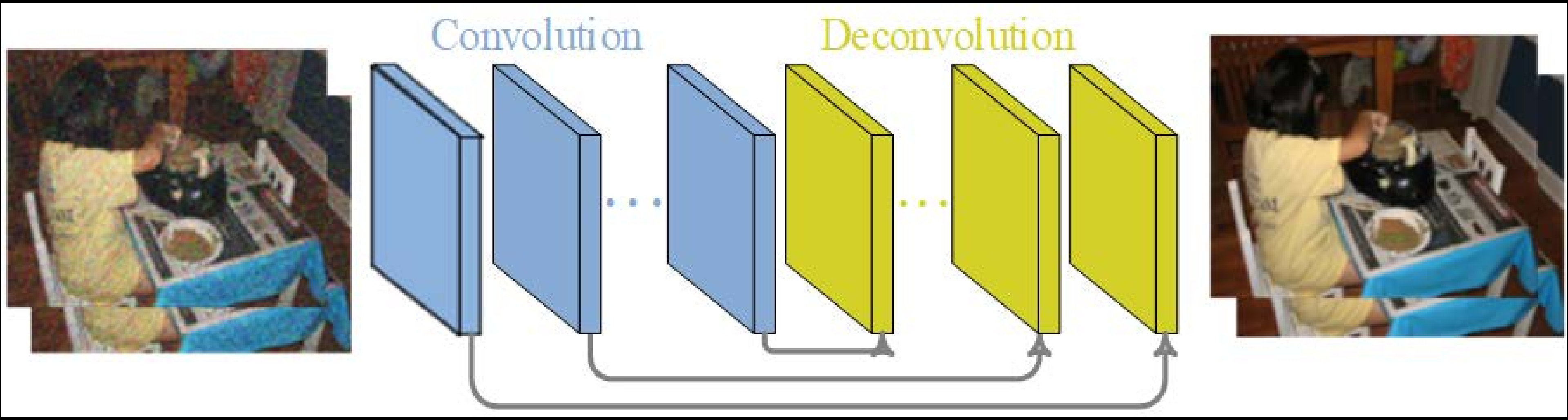
Network and prior learning: 6-D implementation

The network architecture used for learning a DAE in this work is the residual encoder-decoder network (RED-Net).



$$A_{\sigma_\eta}(I(u))$$

The network consists of 10 convolutional and 10 deconvolutional layers symmetrically arranged. Shortcuts connect matching convolutional and deconvolutional layers.

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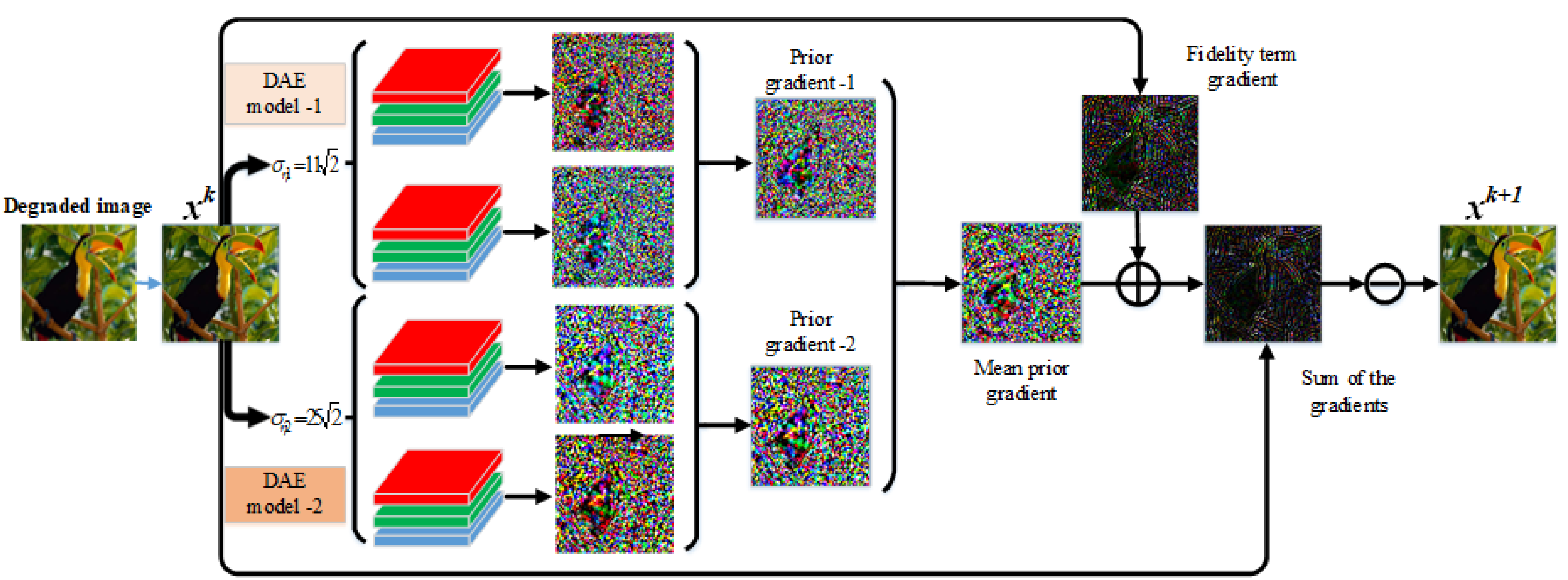
M^2DAEP for SISR

Flowchart of employing the learned M^2EDAP to SISR application.



$$\min_{u} \|Hu - f\|^2 + \frac{\lambda}{N} \sum_{i=1}^{N} \left\| I(u) - A_{\sigma_{\eta i}}(I(u)) \right\|^2$$

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Proposed IR solver

- Considering the 6D and multi-models (N=2), the general mathematical model for color IR can be derived as follows:

$$\min_u \|Hu - f\|^2 + \frac{\lambda}{N}\sum_{i=1}^{N}\left\| I(u) - A_{\sigma_{\eta i}}(I(u))\right\|^2$$

★ $I(u) = [u, u_1]$

★ N stands for the number of M^2DAEP model

★ The first term is the data-fidelity term

★ The second term consists of the network-driven prior information

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Proposed IR solver

- Due to the nonlinearity of the model, we apply the proximal gradient method to tackle it. The model is approximated by standard least square (LS) minimization:

$$\min_{u} \|Hu - f\|^2 + \frac{\lambda}{\beta N} \sum_{i=1}^{N} \left\| I - (I^k - \beta \nabla G_i(I^k)) \right\|^2$$

★ $G_i(I) = \left\| I - A_{\sigma_{\eta_i}}(I) \right\|^2$

★ $\nabla G_i(I) = [1 - \nabla_I A^T_{\sigma_{\eta_i}}(I)][I - A_{\sigma_{\eta_i}}(I)]$

★ The function $G(I)$ is $1/\beta$-Lipschitz smooth

★ $\left\| \nabla G(I^{'}) - \nabla G(I^{''}) \right\|_2 \le \left\| I^{'} - I^{''} \right\|_2 / \beta$ denotes the index number of iterations

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Proposed IR solver

- Given β=1, The above formula can be solved by calculating the gradient as follows:

$$H^T(Hu - f) + \lambda\{I + \frac{1}{N}\sum_{i=1}^{N}[\nabla_I A_{\sigma_{\eta_i}}^T(I^k)(A_{\sigma_{\eta_i}}(I^k) - I^k) - A_{\sigma_{\eta_i}}(I^k)]\} = 0$$

$$u^{k+1} = \frac{H^T f + \frac{\lambda}{N}\sum_{i=1}^{N} R[\{A_{\sigma_{\eta i}}(I^k) - \nabla_I A_{\sigma_{\eta i}}^T(I^k)[A_{\sigma_{\eta i}}(I^k) - I^k]\}]}{(H^T H + \lambda)}$$

★ R stands for the mean operator employed on the six channels.

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Proposed IR solver

★ $A_{\sigma_{\eta i}}(I^k)$ is the forward output with the input $I^k+\sigma_\eta$.

★ $A_{\sigma_{\eta i}}(\circ)$ are already learned at the network training stage.

★ $\nabla_I A^T_{\sigma_{\eta i}}(I^k)[A_{\sigma_{\eta i}}(I^k)-I^k]$ is the backward network output with the input $A_{\sigma_{\eta i}}(I^k)-I^k$.

★ Update the solution u^k by alternately updating the network estimation $A_{\sigma_{\eta i}}(I^k)$, $\nabla_I A^T_{\sigma_{\eta i}}(I^k)$ and LS solver until the u value convergences.

★ The mathematical model is tackled by the proximal gradient and alternative optimization.

Algorithm: M^2DEAP

Training stage

Training images: 6-dimensional dataset $\{I \mid I(u)=[u,u_1]\}$

Noisy levels: $\delta_{\eta 1}$ and $\delta_{\eta 2}$

Network: 6-channel DAE network

Outputs: Trained network $A_{\sigma_{\eta 1}}(\text{o})$ and $A_{\sigma_{\eta 2}}(\text{o})$

Testing stage

Initialization: $u^0=H^Tf$; K; $N=2$

For $k=1, 2, \cdots, K$

Update the auxiliary variable: $I^k=[u^k,u_1^k]$

Calculate the prior gradient components:

$A_{\sigma_{\eta i}}(I^k)$, $\nabla_I A^T_{\sigma_{\eta i}}(I^k)[A_{\sigma_{\eta i}}(I^k)-I^k]$; $i=1,2,\cdots,N$

Update the solution via solving the LS problem:

$$u^{k+1}=\frac{H^Tf+\frac{\lambda}{N}\sum_{i=1}^{N}R[\{A_{\sigma_{\eta i}}(I^k)-\nabla_I A^T_{\sigma_{\eta i}}(I^k)[A_{\sigma_{\eta i}}(I^k)-I^k]\}]}{(H^TH+\lambda)}$$

End

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Part III – Experimental Results:

Single Image Super-Resolution
Image Deblurring

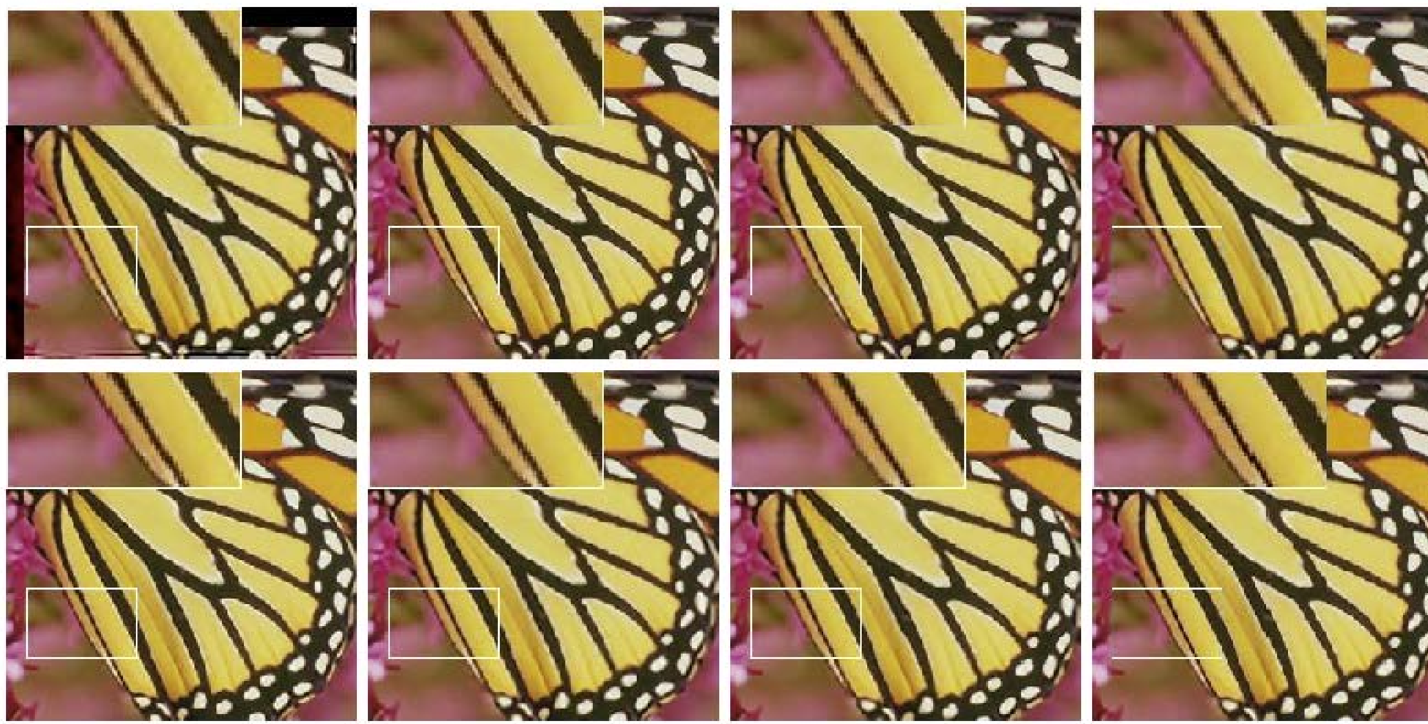
Experimental Results: SISR

Table 1. Average PSNR (dB) of different methods on Set 5 for the different scale factors.

Scale	Dataset	Bicubic	SRCNN	TNRD	DnCNN-3	IRCNN	DMSP	SRMD	DAEP	MDAEP	M²DAEP
×2	Set 5	31.80	34.50	34.62	35.20	35.07	35.16	35.28	35.23	35.41	**35.48**
×3		28.67	30.84	31.08	31.58	31.25	31.38	**31.84**	31.44	31.68	31.75
×4		26.73	28.60	28.83	29.30	29.00	29.14	**29.64**	29.01	29.25	29.44
×5		25.32	26.12	26.88	26.30	27.13	27.35	-	27.19	27.40	**27.59**

From top to bottom and left to right:

SRCNN,
DnCNN-3,
IRCNN,
DMSP,
SRMD,
DAEP
and M^{2}DAEP.



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Experimental Results: Image deblurring

Table 2. The deblurring performance (PSNR) on four images.

Noisy	image	EPLL	DMSP	DAEP	M²DAEP
7.65	Barbara	20.10	**21.23**	20.66	21.10
	Butterfly	19.03	20.18	25.45	**26.97**
	House	24.05	25.45	25.47	**29.01**
	Lena	23.56	26.97	27.37	**28.68**
	Average	21.69	23.45	24.47	**26.07**
12.75	Barbara	19.59	**20.21**	19.33	19.54
	Butterfly	18.81	19.52	22.68	**23.47**
	House	22.57	26.25	24.74	**28.54**
	Lena	24.91	24.25	25.94	**27.45**
	Average	21.47	22.56	23.17	**24.75**

M^2DAEP achieves the highest values for almost images.

M^2DAEP produces cleaner and sharper image edges and textures than other competing methods.

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Part III – Conclusions

Conclusions: Enhanced DAEP for color IR

- Presented a ***6-channel denoising autoencoder prior***, which built on the assumption that an optimal denoising autoencoder is a local mean of the correct data density.

- ***Auxiliary variables technique*** was applied to integrate higher-dimensional structural information.

- This work paved a new way to incorporate ***higher-dimensional prior*** information into color IR applications.

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Thanks all!

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School of Information Engineering

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研究兴趣：Dictionary learning , compressed sensing , Image Processing , Deep Learning

Love to imaging science!

Code

Code of TDAEP (Transformed Denoising Autoencoding Priors for Imaging Inverse Problems)

Code of MWDMSP (Multi-Wavelet Guided Deep Mean-shift Prior for Image Restoration)

Code of M2DAEP (High-dimensional embedding denoising autoencoding prior for color Image restoration)

Code of MEDAEP (Multi-channels and Multi-models based Autoencoding Priors for Grayscale Image Restoration)

Code of VST-Net (VST-Net: Variance-stabilizing Transformation Inspired Network for Poisson Denoising)

Code of EDAEPRec (Highly Undersampled Magnetic Resonance Imaging Reconstruction using Autoencoding Priors)

Code of RicianNet (Progressively distribution-based Rician noise removal for magnetic resonance imaging)

Code of MDAEP-SR (Learning Multi-Denoising Autoencoding Priors for Image Super-Resolution)

Code of Iterative-scheme Inspired Network (Iterative-scheme Inspired Network for Impulse Noise Removal)

- **Code:** https://github.com/yqx7150/M2DAEP
- **Code:** http://www.escience.cn/people/liuqiegen

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