Uncertainty-Driven Loss for Single Image Super-Resolution

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Motivation

The loss function in most of existing deep-learning methods is MSE/L1 loss.

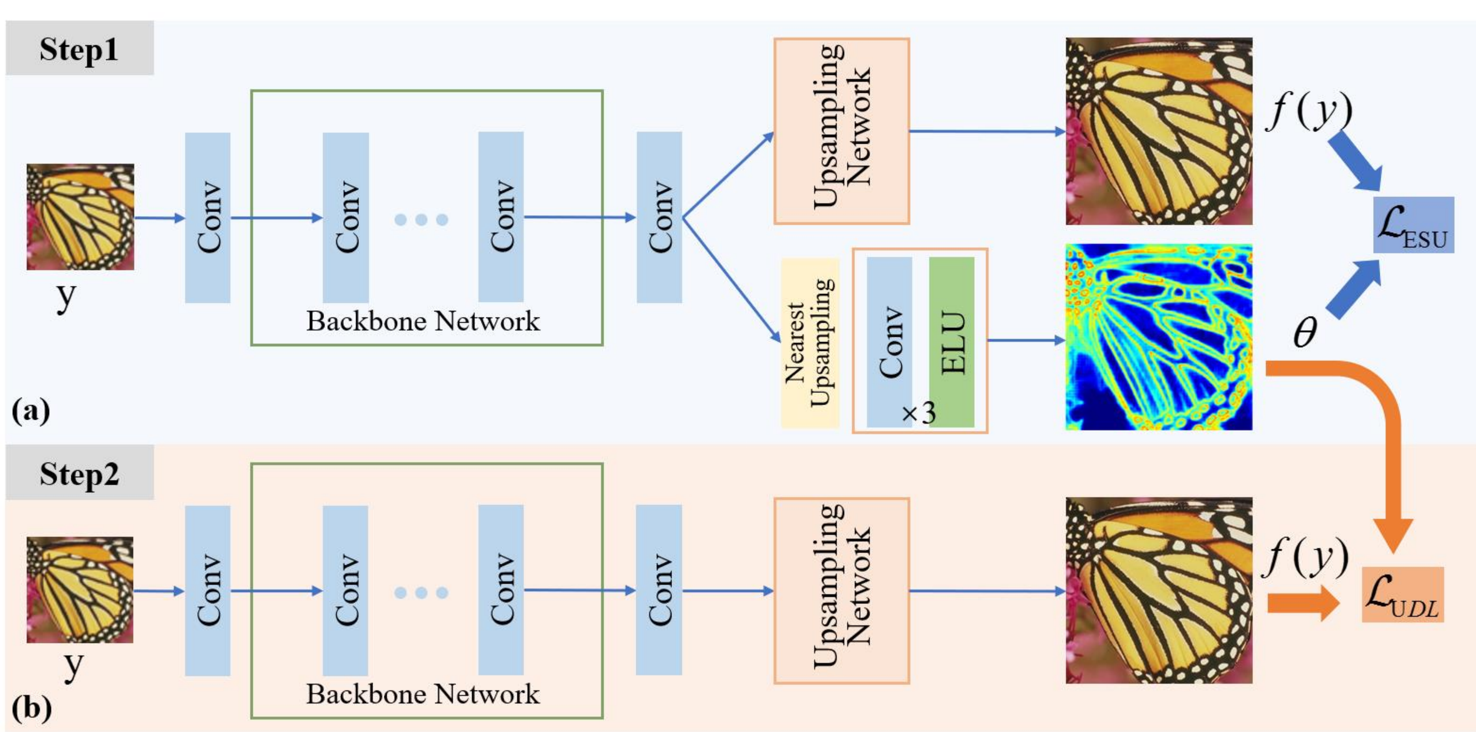
$$p(\boldsymbol{x} \mid \boldsymbol{y}, \boldsymbol{W}) = \prod_{l=1}^{M} c \exp\left(-\frac{\|\boldsymbol{x}^{(l)} - f^{(\boldsymbol{W})}(\boldsymbol{y}^{(l)})\|_1}{\sigma}\right),$$

where c, σ denote spatially invariant constants.

(a) *Img_001* from Set14 (b) HR image $\boldsymbol{x}$ (c) SR image $f(\boldsymbol{y})$ (d) Difference map $|\boldsymbol{x} - f(\boldsymbol{y})|$

- However, such assumption of stationarity or spatial invariance of image prior model is invalid for photographic images in the real world.
- From Fig. (c) and (d), it can be observed that texture areas (e.g., hair of baboon) are not restored as good as smooth areas (e.g., nose of baboon). That means the variance of texture and edge areas is much larger than that in smooth areas.
- Based on above observation, we proposed to estimate the mean and variance together in SISR.

Training Process



Contributions

- We propose to cast SISR into a Bayesian framework under which SR image (mean) and uncertainty (variance) are derived simultaneously.
- The estimation of variance map facilitates the training of SISR network by dividing it into two steps. In the first step, an estimating sparsity uncertainty (ESU) loss function was proposed to estimate the variance map. In the second step, the estimated variance map serves as the guidance signal leading to adaptive weighted loss named uncertainty-driven loss LUDL.
- The proposed uncertainty loss can easily be employed in any SISR network.
- The proposed loss has achieved better performance than MSE or L1 loss.

Methodology

Estimating Uncertainty (EU) in SISR.

For a given LR image y_i and corresponding HR image x_i, a Laplace distribution is assumed for characterizing the likelihood function by:

$$p(\boldsymbol{x}_i, \boldsymbol{\theta}_i | \boldsymbol{y}_i) = \frac{1}{2\,\boldsymbol{\theta}_i} \exp\left(-\frac{\|\boldsymbol{x}_i - f(\boldsymbol{y}_i)\|_1}{\boldsymbol{\theta}_i}\right),$$

The log likelihood: $$\ln p(\boldsymbol{x}_i, \boldsymbol{\theta}_i | \boldsymbol{y}_i) = -\frac{\|\boldsymbol{x}_i - f(\boldsymbol{y}_i)\|_1}{\boldsymbol{\theta}_i} - \ln \boldsymbol{\theta}_i - \ln 2$$

The loss function: $$\mathcal{L}_{EU} = \frac{1}{N}\sum_{i=1}^{N} \exp(-\boldsymbol{s}_i)\, \|\boldsymbol{x}_i - f(\boldsymbol{y}_i)\|_1 + \boldsymbol{s}_i$$

$$\boldsymbol{s}_i = \ln \boldsymbol{\theta}_i$$

Estimating Sparse Uncertainty (ESU) in SISR.

$$p(\boldsymbol{x}_i, \boldsymbol{\theta}_i | \boldsymbol{y}_i) = p(\boldsymbol{x}_i | \boldsymbol{y}_i, \boldsymbol{\theta}_i) p(\boldsymbol{\theta}_i) \propto \frac{1}{2\,\boldsymbol{\theta}_i} \exp\left(-\frac{\|\boldsymbol{x}_i - f(\boldsymbol{y}_i)\|_1}{\boldsymbol{\theta}_i}\right) \frac{1}{\boldsymbol{\theta}_i} = \frac{1}{2\,\boldsymbol{\theta}_i^2} \exp\left(-\frac{\|\boldsymbol{x}_i - f(\boldsymbol{y}_i)\|_1}{\boldsymbol{\theta}_i}\right)$$

The log likelihood: $$\ln p(\boldsymbol{x}_i | \boldsymbol{y}_i) = -\frac{\|\boldsymbol{x}_i - f(\boldsymbol{y}_i)\|_1}{\boldsymbol{\theta}_i} - 2 \ln \boldsymbol{\theta}_i - \ln 2$$

The loss function: $$\mathcal{L}_{ESU} = \frac{1}{N}\sum_{i=1}^{N} \exp(-\boldsymbol{s}_i)\, \|\boldsymbol{x}_i - f(\boldsymbol{y}_i)\|_1 + 2\,\boldsymbol{s}_i$$

$$\boldsymbol{s}_i = \ln \boldsymbol{\theta}_i$$

(a) HR (b) EDSR-S (c) EDSR-S-$\mathcal{L}_{EU}$ (d) EDSR-S-$\mathcal{L}_{ESU}$ (e) $\mathcal{L}_{EU}$ Uncertainty (f) $\mathcal{L}_{ESU}$ Uncertainty

The limitations of L_{EU} and L_{ESU} loss.

Base Model	Scale	Loss	Set5 [23]		Set14 [8]		BSD100 [24]		Urban100 [25]		Manga109 [26]	
			PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
EDSR-S[2]	×4	Original	**30.93**	**0.8740**	**27.80**	**0.7627**	**27.05**	**0.7190**	**24.71**	**0.7351**	**28.14**	**0.8693**
		$\mathcal{L}_{EU}$	30.19	0.8627	27.29	0.7538	26.78	0.7120	24.21	0.7179	26.78	0.8481
		$\mathcal{L}_{ESU}$	30.31	0.8637	27.39	0.7543	26.83	0.7124	24.27	0.7192	26.92	0.8496

However, Applying LEU or LESU loss leads to more accurate estimation of uncertainty (variance field), but counter-intuitively, they do not directly improve the performance of SISR.

Uncertainty-Driven Loss (UDL) for SISR

Instead of using $\exp(-s_i)$ to **attenuate** the importance of pixels with large uncertainty, we need to use a monotonically increasing function to **prioritize** them.

$$\mathcal{L}_{UDL} = \frac{1}{N}\sum_{i=1}^{N} \hat{\boldsymbol{s}}_i\, \|\boldsymbol{x}_i - f(\boldsymbol{y}_i)\|_1,$$

$$\hat{\boldsymbol{s}}_i = \boldsymbol{s}_i - \min(\boldsymbol{s}_i)$$

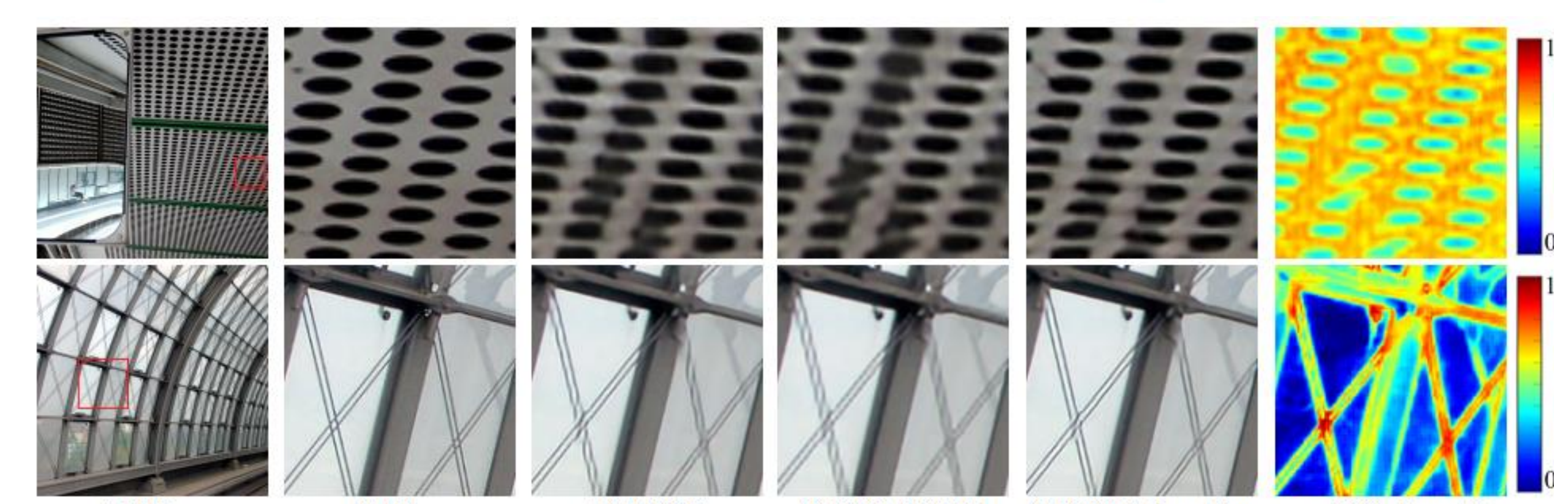
Results

Base Model	Scale	Loss	Set5 [22]		Set14 [8]		BSD100 [23]		Urban100 [24]		Manga109 [25]	
			PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
EDSR-S [2]	×2	Original	37.66	0.8594	33.22	0.9146	31.95	0.8969	30.71	0.9205	37.79	0.9752
		GRAM [20]	37.48	0.9589	32.99	0.9126	31.76	0.8946	30.11	0.9134	37.38	0.9739
		$\mathcal{L}_{UDL}$-Ours	**37.95**	**0.9604**	**33.50**	**0.9165**	**32.13**	**0.8991**	**31.54**	**0.9304**	**38.38**	**0.9767**
DPDNN [3]	×2	Original	37.75	0.9600	33.30	0.9150	32.09	0.8990	31.50	0.9220	-	-
		GRAM [20]	37.74	0.9597	33.27	0.9148	31.98	0.8973	30.97	0.9238	38.14	0.9758
		$\mathcal{L}_{UDL}$-Ours	**38.00**	**0.9605**	**33.63**	**0.9176**	**32.16**	**0.8995**	**31.72**	**0.9331**	**38.55**	**0.9769**
EDSR [2]	×2	Original	38.11	0.9602	33.92	0.9195	32.32	0.9013	32.93	0.9351	39.10	0.9773
		GRAM [20]	37.87	0.9604	33.43	0.9164	32.08	0.8990	31.46	0.9301	37.91	0.9765
		$\mathcal{L}_{UDL}$-Ours	**38.29**	**0.9615**	**34.14**	**0.9236**	**32.40**	**0.9027**	**32.99**	**0.9446**	**39.53**	**0.9787**
EDSR-S [2]	×3	Original	33.90	0.9231	29.95	0.8352	28.85	0.7996	27.30	0.8344	32.52	0.9369
		GRAM [20]	33.27	0.9178	29.60	0.8298	28.60	0.7936	26.52	0.8142	31.14	0.9258
		$\mathcal{L}_{UDL}$-Ours	**34.15**	**0.9251**	**30.15**	**0.8388**	**28.99**	**0.8021**	**27.72**	**0.8430**	**32.97**	**0.9406**
DPDNN [3]	×3	Original	33.93	0.9240	30.02	0.8360	29.00	0.8010	27.61	0.8420	-	-
		GRAM [20]	33.92	0.9241	30.00	0.8362	28.86	0.8000	27.37	0.8353	32.41	0.9373
		$\mathcal{L}_{UDL}$-Ours	**34.30**	**0.9267**	**30.31**	**0.8419**	**29.10**	**0.8047**	**28.02**	**0.8505**	**33.27**	**0.9435**
EDSR [2]	×3	Original	34.65	0.9280	30.52	0.8462	29.25	0.8093	28.80	0.8653	34.17	0.9476
		GRAM [20]	34.34	0.9270	30.28	0.8412	29.07	0.8044	27.98	0.8789	33.32	0.9432
		$\mathcal{L}_{UDL}$-Ours	**34.83**	**0.9312**	**30.69**	**0.8497**	**29.28**	**0.8109**	**28.99**	**0.8697**	**34.63**	**0.9502**
EDSR-S [2]	×4	Original	31.61	0.8862	28.22	0.7721	27.30	0.7271	25.25	0.7575	29.31	0.8907
		GRAM [20]	31.08	0.8787	27.89	0.7670	27.12	0.7229	24.81	0.7429	28.18	0.8762
		$\mathcal{L}_{UDL}$-Ours	**31.90**	**0.8897**	**28.37**	**0.7755**	**27.40**	**0.7301**	**25.54**	**0.7671**	**29.77**	**0.8967**
DPDNN [3]	×4	Original	31.72	0.8890	28.28	0.7730	27.44	0.7290	25.53	0.7680	-	-
		GRAM [20]	31.89	0.8913	28.37	0.7772	27.41	0.7314	25.63	0.7708	29.70	0.9003
		$\mathcal{L}_{UDL}$-Ours	**32.20**	**0.8944**	**28.60**	**0.7819**	**27.56**	**0.7356**	**26.09**	**0.7862**	**30.38**	**0.9082**
EDSR [2]	×4	Original	32.46	0.8968	28.80	0.7876	27.71	0.7420	26.64	0.8033	31.02	0.9148
		GRAM [20]	32.32	0.8971	28.73	0.7858	27.66	0.7395	26.35	0.7955	30.73	0.9125
		$\mathcal{L}_{UDL}$-Ours	**32.59**	**0.8998**	**28.87**	**0.7889**	**27.78**	**0.7431**	**26.75**	**0.8054**	**31.24**	**0.9167**

Weighted loss	Set5	Δ	Set14	Δ	BSD100	Δ	Urban100	Δ	Manga109	Δ
Baseline	31.61	0.00	28.22	0.00	27.30	0.00	25.25	0.00	29.31	0.00
Uncertainty(Ours)	**31.90**	**0.29↑**	**28.37**	**0.15↑**	**27.40**	**0.10↑**	**25.54**	**0.29↑**	**29.77**	**0.46↑**
Error_map	31.77	0.16↑	28.30	0.08↑	27.35	0.05↑	25.40	0.15↑	29.57	0.26↑
HR_gradient_map	31.68	0.07↑	28.27	0.05↑	27.35	0.05↑	25.42	0.17↑	29.45	0.14↑
LR_gradient_map	31.69	0.08↑	28.29	0.07↑	27.35	0.05↑	25.38	0.13↑	29.50	0.19↑

Visual Quality Comparisons

(a) *Img_095* (b) HR (c) DPDNN (d) DPDNN-GRAM (e) DPDNN-$\mathcal{L}_{UDL}$-Ours (f) Our Uncertainty



(a) HR (b) HR (c) EDSR-S (d) EDSR-S-GRAM (e) EDSR-S-$\mathcal{L}_{UDL}$-Ours (f) Our Uncertainty

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