Perceptually-Optimized Loss Function for Image Super-Resolution

Amirhossein Arezoomand [1]   Pooryaa Cheraaqee [1]   Azadeh Mansouri [1]

[1]**Department of**
Electrical and Computer Engineering,
Kharazmi University

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Outline

1. Problem Definition
   - Image Super-Resolution
   - Loss Function

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2. Previous Attempts
3. The Taken Approach

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   - Image Super-Resolution
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4. Results
   - Qualitative
   - Quantitative

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What is *Super-Resolution*?

- increasing the dimension

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  - input $(X_{M \times N}) \xrightarrow{\text{upsampling by a factor of 2 (i.e. } 2\uparrow)}$ output $(Y_{2M \times 2N})$

What is *Super-Resolution*?

- increasing the dimension
  - input ($X_{M \times N}$) $\xrightarrow{\text{upsampling by a factor of 2 (i.e. } 2\uparrow)}$ output ($Y_{2M \times 2N}$)
  - BiLinear, BiCubic, etc.

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- **!! Preserving the quality !!**

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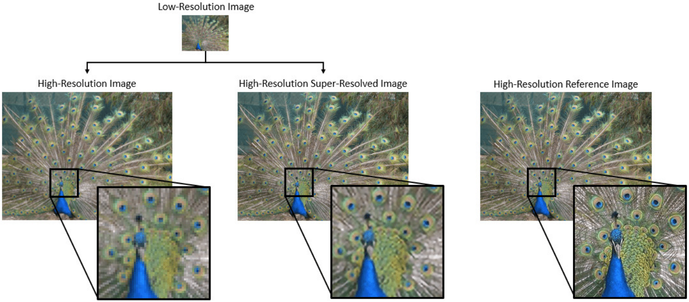
- **!! Preserving the quality !!**



CNNs and Loss Functions

- Super-Resolver CNNs

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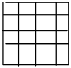

Input patch

CNNs and Loss Functions

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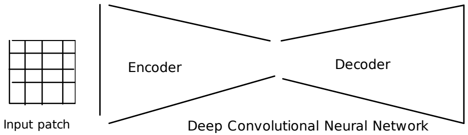

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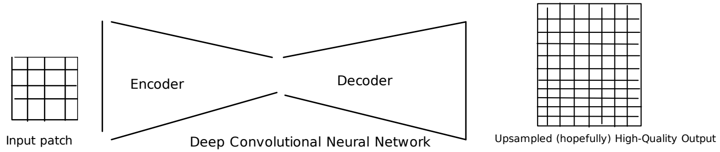

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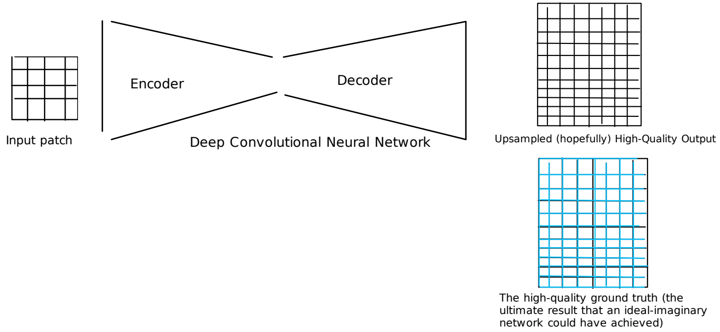

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  $W \rightarrow$ Current network's weight

CNNs and Loss Functions

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  $W \rightarrow$ Current network's weight
  $Y = F(X, W)$

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  The amount of update that must be applied to W $(i.e. \Delta W) = E(Y, \hat{Y})$; where $E \in [0, 1]$

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  $X \rightarrow$ Network's input

  $\hat{Y} \rightarrow$ Network's output

  $Y \rightarrow$ The correct answer

  $W \rightarrow$ Current network's weight

  $Y = F(X, W)$

  The amount of update that must be applied to W $(i.e. \Delta W) = E(Y, \hat{Y})$; where $E \in [0, 1]$

  The updated network's weights $(i.e. W\prime) = W + \Delta W$

CNNs and Loss Functions

- Super-Resolver CNNs
- The Loss Function
  How to define $E(Y, \hat{Y})$?

Ways to Define a Loss Function

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- Visible Error

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$$E(Y,\hat{Y}) = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(Y(i,j) - \hat{Y}(i,j))^2$$

Ways to Define a Loss Function

- Visible Error

$$E(Y, \hat{Y}) = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (Y(i,j) - \hat{Y}(i,j))^2$$

- Quality Metrics

Ways to Define a Loss Function

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$E(Y, \hat{Y}) = SSIM(Y, \hat{Y})$[1]

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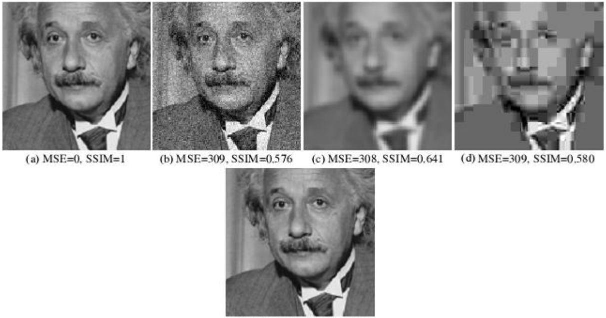
- Quality Metrics

$E(Y, \hat{Y}) = SSIM(Y, \hat{Y})[1]$



(a) MSE=0, SSIM=1 (b) MSE=309, SSIM=0.576 (c) MSE=308, SSIM=0.641 (d) MSE=309, SSIM=0.580

(e) MSE=871, SSIM=0.404

Our Method

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  - Expressive

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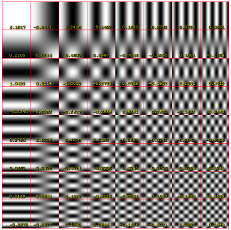

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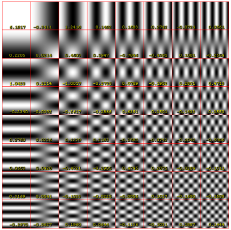

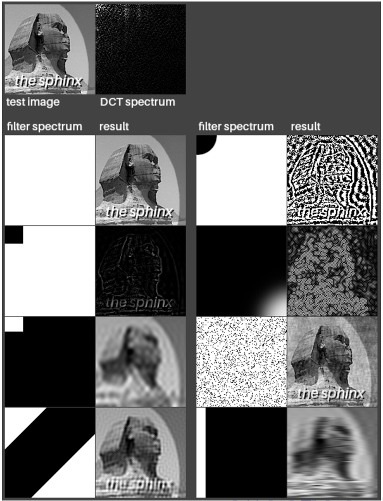

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16	11	10	16	24	40	51	61
12	12	14	19	26	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
18	22	37	56	68	109	103	77
24	35	55	64	81	104	113	92
49	64	78	87	103	121	120	101
72	92	95	98	112	100	103	99

The Proposed Loss Function

$Y, \hat{Y} \rightarrow [0, 1]$

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$Y, \hat{Y} \rightarrow [0, 1]$

$\xrightarrow{(1)}$ compute $DCT(Y)$ and $DCT(\hat{Y})$

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$Y, \hat{Y} \to [0, 1]$

$\xrightarrow{(1)}$ compute $DCT(Y)$ and $DCT(\hat{Y})$
$\xrightarrow{(2)}$ quantize $DCT(Y)$ and $DCT(\hat{Y})$

The Proposed Loss Function

$Y, \hat{Y} \rightarrow [0, 1]$

$\xrightarrow{(1)}$ compute $DCT(Y)$ and $DCT(\hat{Y})$
$\xrightarrow{(2)}$ quantize $DCT(Y)$ and $DCT(\hat{Y})$
$\xrightarrow{(3)}$ compute the visible error between the quantized coefficients

The Proposed Loss Function

$\xrightarrow{(2)}$ quantize $DCT(Y)$ and $DCT(\hat{Y})$

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16	11	10	16	24	40	51	61
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14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
18	22	37	56	68	109	103	77
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$\xrightarrow{(2)}$ quantize $DCT(Y)$ and $DCT(\hat{Y})$

16	11	10	16	24	40	51	61
12	12	14	19	26	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
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49	64	78	87	103	121	120	101
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$\xrightarrow{\textit{upsample}}$

16	16	14	12	11	10	10	12	14	17	20	23	28	34	40	44	49	53	56	60	61
16	15	14	12	11	10	10	12	15	17	20	23	28	35	41	45	49	53	56	60	60
14	14	13	12	11	11	12	14	16	18	21	24	31	40	48	51	53	56	57	58	58
13	13	12	12	12	12	13	15	17	19	22	25	33	44	55	56	58	58	57	56	56
12	12	12	12	13	13	14	16	18	21	24	28	37	47	58	59	61	61	58	55	55
13	13	13	13	13	14	15	17	20	23	28	33	40	49	57	61	64	64	60	56	56
14	14	13	13	14	15	16	19	22	26	32	38	44	51	57	62	66	66	62	57	56
14	14	14	14	15	17	18	21	24	28	35	42	50	59	68	70	72	70	65	59	58
14	14	15	15	17	18	20	23	26	30	38	45	56	68	79	78	77	74	68	61	60
14	15	16	17	19	21	24	27	30	35	42	50	62	76	89	87	84	80	72	65	64
16	16	17	19	22	25	29	34	39	44	51	57	69	84	98	95	93	88	79	71	70
17	18	19	21	24	29	35	41	48	54	59	64	76	92	106	104	101	96	86	77	75
20	20	22	24	29	35	41	47	54	60	65	70	81	95	108	107	106	101	92	82	81
22	22	26	29	34	41	48	53	58	63	69	75	84	95	106	107	108	105	97	88	86
24	25	30	34	40	47	55	59	62	66	73	79	87	96	104	108	111	110	102	94	92
34	35	40	44	50	57	64	67	71	75	81	88	95	103	111	113	115	112	105	97	96
43	45	50	55	61	67	73	76	79	84	90	96	103	111	117	118	118	115	108	100	99
53	54	60	66	71	76	80	83	87	91	96	103	108	113	117	117	117	114	108	102	100
61	63	69	76	81	84	87	89	92	95	100	106	108	109	109	110	110	109	105	101	100
70	72	79	87	91	92	94	95	96	99	104	109	109	105	101	102	104	103	101	99	99
72	73	81	88	92	94	95	96	97	100	105	110	109	104	100	101	102	102	101	99	99

The Proposed Loss Function

$\xrightarrow{(2)}$ quantize $DCT(Y)$ and $DCT(\hat{Y})$

16	11	10	16	24	40	51	61
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$Q_l = \alpha \cdot \uparrow (Q)$

$\xrightarrow{\textit{upsample}}$

16	16	14	12	11	10	10	12	14	17	20	23	28	34	40	44	49	53	56	60	61
16	15	14	12	11	10	10	12	15	17	20	23	28	35	41	45	49	53	56	60	60
14	14	13	12	11	11	12	14	16	18	21	24	31	40	48	51	53	56	57	58	58
13	13	12	12	12	12	13	15	17	19	22	25	33	44	55	56	58	58	57	56	56
12	12	12	12	13	13	14	16	18	21	24	28	37	47	58	59	61	61	58	55	55
13	13	13	13	13	14	15	17	20	23	28	33	40	49	57	61	64	64	60	56	56
14	14	13	13	14	15	16	19	22	26	32	38	44	51	57	62	66	66	62	57	56
14	14	14	14	15	17	18	21	24	28	35	42	50	59	68	70	72	70	65	59	58
14	14	15	15	17	18	20	23	26	30	38	45	56	68	79	78	77	74	68	61	60
14	15	16	17	19	21	24	27	30	35	42	50	62	76	89	87	84	80	72	65	64
16	16	17	19	22	25	29	34	39	44	51	57	69	84	98	95	93	88	79	71	70
17	18	19	21	24	29	35	41	48	54	59	64	76	92	106	104	101	96	86	77	75
20	20	22	24	29	35	41	47	54	60	65	70	81	95	108	107	106	101	92	82	81
22	22	26	29	34	41	48	53	58	63	69	75	84	95	106	107	108	105	97	88	86
24	25	30	34	40	47	55	59	62	66	73	79	87	96	104	108	111	110	102	94	92
34	35	40	44	50	57	64	67	71	75	81	88	95	103	111	113	115	112	105	97	96
43	45	50	55	61	67	73	76	79	84	90	96	103	111	117	118	118	115	108	100	99
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72	73	81	88	92	94	95	96	97	100	105	110	109	104	100	101	102	102	101	99	99

The Proposed Loss Function

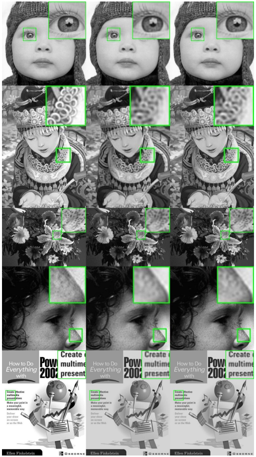
$Y, \hat{Y} \rightarrow [0, 1]$

$$\boxed{popSR(Y, \hat{Y}) = \frac{1}{21 \times 21} \sum_{i=1}^{21} \sum_{j=1}^{21} \left(\frac{DCT\left(Y\right)(i,j)}{Q_l(i,j)} - \frac{DCT\left(\hat{Y}\right)(i,j)}{Q_l(i,j)} \right)^2}$$

Experimental Setup

- train SRCNN [2] with MSE
- train SRCNN with popSR
- Timofte et. al [3] for train
- Set5 [4] Set14 [5] for test on various scales

Sample Outputs



Sample Outputs

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Objective Evaluation

- Three metrics:
  - PSNR
  - SSIM
  - GMSD [6]
- Two datasets:
  - set5
  - set14
- 3 scaling factors
  - 2 $\uparrow$
  - 3 $\uparrow$
  - 4 $\uparrow$

Objective Evaluation

set5 & 2 $\uparrow$

	Proposed Loss Function			MSE Loss Function		
Set5 Dataset	PSNR	SSIM	GMSD	PSNR	SSIM	GMSD
Baby	**37.28**	**0.96**	**0.075**	36.53	0.95	0.077
Butterfly	28.06	**0.92**	**0.111**	**29.87**	0.90	0.120
Bird	34.21	**0.96**	**0.076**	**36.13**	**0.96**	0.078
Head	**34.10**	**0.88**	**0.078**	31.91	0.83	0.082
Woman	**34.90**	**0.96**	**0.086**	28.80	0.94	0.092
Average	**33.71**	**0.94**	**0.085**	32.65	0.92	0.090

Objective Evaluation

set5 & 3 $\uparrow$

	Proposed Loss Function			MSE Loss Function		
Set5 Dataset	PSNR	SSIM	GMSD	PSNR	SSIM	GMSD
Baby	**34.68**	**0.91**	**0.090**	30.01	0.86	0.099
Butterfly	**29.70**	**0.85**	**0.129**	28	0.73	0.140
Bird	31.67	**0.93**	**0.091**	**32.40**	0.84	0.102
Head	**32.86**	**0.80**	**0.098**	31.90	0.72	0.109
Woman	**33.43**	**0.91**	**0.099**	28.75	0.83	0.113
Average	**32.34**	**0.88**	**0.101**	30.21	0.80	0.113

Objective Evaluation

set5 & 4 $\uparrow$

	Proposed Loss Function			MSE Loss Function		
Set5 Dataset	PSNR	SSIM	GMSD	PSNR	SSIM	GMSD
Baby	**33.48**	**0.85**	**0.098**	32.48	0.85	0.100
Butterfly	**29.79**	**0.78**	**0.137**	28.07	0.73	0.142
Bird	28.77	0.85	**0.102**	**29.88**	**0.86**	0.105
Head	**32.03**	**0.74**	**0.109**	31.94	0.74	0.111
Woman	**32.48**	**0.85**	**0.108**	28.73	0.82	0.113
Average	**31.31**	**0.81**	**0.111**	30.22	0.80	0.114

Objective Evaluation

set14 & 2 $\uparrow$

	Proposed Loss Function			MSE Loss Function		
Set14 Dataset	PSNR	SSIM	GMSD	PSNR	SSIM	GMSD
Baboon	**27.77**	**0.74**	**0.133**	27.75	0.70	0.137
Barbara	**32.86**	**0.85**	**0.106**	31.54	0.82	0.109
Bridge	28.99	**0.84**	**0.120**	**29.26**	0.81	0.125
Coastguard	**30**	**0.82**	**0.118**	29.43	0.77	0.121
Comic	**28.62**	**0.88**	**0.120**	27.92	0.84	0.127
Face	**34.10**	**0.88**	**0.078**	31.92	0.84	0.082
Flowers	**29.98**	**0.90**	**0.098**	29.43	0.88	0.101
Foreman	**29.54**	**0.94**	**0.079**	28.90	0.92	0.084
Lena	**34.9**	**0.91**	**0.073**	29.94	0.89	0.080
Man	**28.46**	**0.79**	**0.102**	27.73	0.75	0.107
Monarch	**27.46**	**0.95**	**0.077**	26.76	0.94	0.082
Pepper	**27.82**	**0.89**	**0.069**	27.81	0.88	0.072
PPT3	28.11	**0.88**	**0.081**	**28.12**	0.86	0.090
Zebra	**29.28**	**0.90**	**0.101**	28.98	0.86	0.104
Average	**29.85**	**0.87**	**0.097**	28.96	0.84	0.102

Objective Evaluation

set14 & 3 $\uparrow$

	Proposed Loss Function			MSE Loss Function		
Set14 Dataset	PSNR	SSIM	GMSD	PSNR	SSIM	GMSD
Baboon	**29.52**	**0.58**	**0.150**	27.81	0.50	0.156
Barbara	**31.67**	**0.76**	**0.122**	30.57	0.68	0.128
Bridge	**28.65**	**0.70**	**0.140**	28.42	0.60	0.146
Coastguard	**30.38**	**0.61**	**0.142**	28.92	0.51	0.148
Comic	**28.32**	**0.73**	**0.142**	27.92	0.61	0.150
Face	**32.86**	**0.80**	**0.098**	31.91	0.72	0.109
Flowers	**30.93**	**0.81**	**0.117**	28.37	0.71	0.128
Foreman	**30.58**	**0.91**	**0.094**	27.82	0.84	0.107
Lena	**33.77**	**0.86**	**0.090**	30.65	0.80	0.106
Man	28.37	**0.70**	**0.120**	**30.49**	0.68	0.131
Monarch	**30.16**	**0.92**	**0.089**	27.63	0.87	0.100
Pepper	27.74	**0.85**	**0.080**	**31.41**	0.82	0.091
PPT3	27.03	**0.83**	**0.099**	**27.07**	0.78	0.122
Zebra	**30.2**	**0.79**	**0.122**	28	0.69	0.133
Average	**30.01**	**0.78**	**0.115**	29.07	0.70	0.125

Objective Evaluation

set14 & 4 ↑

	Proposed Loss Function			MSE Loss Function		
Set14 Dataset	PSNR	SSIM	GMSD	PSNR	SSIM	GMSD
Baboon	**29.25**	**0.47**	**0.155**	27.78	0.46	0.160
Barbara	**31.02**	**0.68**	**0.127**	29.30	0.67	0.131
Bridge	**29.05**	**0.59**	**0.148**	28.37	0.57	0.149
Coastguard	**29.89**	**0.49**	**0.150**	29.49	0.47	**0.150**
Comic	**29.02**	**0.62**	**0.153**	28.10	0.59	0.156
Face	**32.03**	**0.74**	**0.109**	31.94	**0.74**	0.111
Flowers	**29.51**	**0.72**	**0.128**	28.64	0.69	0.130
Foreman	**29.52**	**0.86**	**0.101**	28.64	0.84	0.105
Lena	**32.78**	**0.81**	**0.100**	30.17	0.79	0.105
Man	27.97	0.62	**0.129**	**29.01**	**0.66**	0.133
Monarch	**27.65**	**0.88**	**0.098**	27.19	0.86	0.100
Pepper	27.90	**0.82**	**0.088**	**28.90**	0.81	0.091
PPT3	28.69	**0.79**	**0.112**	**29.32**	0.77	0.121
Zebra	**29.29**	**0.67**	**0.134**	28.32	0.67	0.137
Average	**29.54**	**0.70**	**0.124**	28.94	0.68	0.127

Conclusions

- Perceptual

Conclusions

- Perceptual
- Portable

Conclusions

- Perceptual
- Portable
- Efficient

Conclusions

- Perceptual
- Portable
- Efficient
- Faster Convergence

Conclusions

- Perceptual
- Portable
- Efficient
- Faster Convergence
- Incorporating Color

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