SoK: Single Image Super-Resolution

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- Edge-based Methods
- Statistical Methods
- Patch-based Methods
- Sparse Dictionary Methods
- GANs-based Methods

Loss Functions
- Pixel Loss
- Perceptual Loss
- Adversarial Loss
- Heatmap Loss

Performance Metrics
- Peak Signal to Ratio (PSNR)
- Structural Similarity Index Measure (SSIM)
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Interpolation-based Methods

FIG. 1. Schematic diagram of the superresolution algorithm. A high-resolution reconstructed image (left) is sought, which gives simulated low-resolution images that are as close as possible to the observed low-resolution images.

[Irani and Peleg, 1991]
Interpolation-based methods (bilinear, bicubic, and Lanczos) generate HR pixel intensities by weighted averaging neighboring LR pixel values. Since interpolated intensities are locally similar to neighboring pixels, these algorithms generate good smooth regions but insufficient large gradients along edges and at high-frequency regions [Yang et al., 2014].
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Edge-based Methods

Several SISR algorithms have been proposed to learn priors from edge features for reconstructing HR images [Yang et al., 2014]. [Fattal, 2007] proposed the depth and width feature of edges. [Sun et al., 2008] suggested using gradient profiles.
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Figure 4: Architecture of Generator and Discriminator Network with corresponding kernel size (k), number of feature maps (n) and stride (s) indicated for each convolutional layer.

[Ledig et al., 2017]
Figure 2: The proposed Super-FAN architecture comprises three connected networks: the first network is a newly proposed Super-resolution network (see sub-section 4.1). The second network is a WGAN-based discriminator used to distinguish between the super-resolved and the original HR image (see sub-section 4.2). The third network is FAN, a face alignment network for localizing the facial landmarks on the super-resolved facial image and improving super-resolution through a newly-introduced heatmap loss (see sub-section 4.3).
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Given a low resolution image $I^{LR}$ and the corresponding high resolution image $I^{HR}$, pixel-wise MSE loss is used to minimize the distance between $I^{LR}$ and $I^{HR}$.

$$l_{\text{pixel}} = \frac{1}{r^2 WH} \sum_{x=1}^{rW} \sum_{y=1}^{rH} (I^{HR}_{x,y} - G_{\theta}G(I^{LR})_{x,y})^2$$ (1)

where $W$ and $H$ denote and size of $I^{LR}$ and $r$ is the upsampling factor.
Perceptual Loss

The pixel-wise MSE loss achieves high PSNR values, however, it often results in blurry and unrealistic images. To address this issue, [Johnson et al., 2016, Ledig et al., 2017] proposed a perceptual loss where the super-resolved image and the original image must also be close in feature space.

Feature Reconstruction Loss

The loss over the ResNet features at a given level $i$ is defined as

$$l_{\text{feature}/i} = \frac{1}{W_i H_i} \sum_{x=1}^{W_i} \sum_{y=1}^{H_i} (\phi_i(I_{HR})_{x,y} - \phi_i(G_{\theta_{\text{G}}}(I_{LR}))_{x,y})^2$$

(2)

where $\phi_i$ denotes the feature map obtained after the last convolutional layer of the $i^{\text{th}}$ block, and $W_i$ and $H_i$ are its size.
Feature Reconstruction Loss

Fig. 3. Similar to [6], we use optimization to find an image $\hat{y}$ that minimizes the feature reconstruction loss $\ell_{feat}^{\phi,j}(\hat{y}, y)$ for several layers $j$ from the pretrained VGG-16 loss network $\phi$. As we reconstruct from higher layers, image content and overall spatial structure are preserved, but color, texture, and exact shape are not.

[Johnson et al., 2016]
Fig. 4. Similar to [10], we use optimization to find an image $\hat{y}$ that minimizes the style reconstruction loss $\ell_{style}^{\phi,j}(\hat{y}, y)$ for several layers $j$ from the pretrained VGG-16 loss network $\phi$. The images $\hat{y}$ preserve stylistic features but not spatial structure.
WGAN Loss

**Wasserstein GAN Loss**

\[
l_{\text{WGAN}} = \mathbb{E}_{\hat{i} \sim \mathbb{P}_g}[D(\hat{i})] - \mathbb{E}_{\hat{i} \sim \mathbb{P}_r}[D(I^{HR})] + \lambda \mathbb{E}_{\hat{i} \sim \mathbb{P}_{\hat{i}}}[(||\nabla_{\hat{i}}D(\hat{i})||_2 - 1)^2]
\]  

(3)

where \( \mathbb{P}_r \) is the data distribution and \( \mathbb{P}_g \) is the generator \( G \) distribution defined by \( \hat{i} = G(I^{LR}) \). \( \mathbb{P}_{\hat{i}} \) is obtained by uniformly sampling along straight lines between pairs of samples from \( \mathbb{P}_r \) and \( \mathbb{P}_g \).
[Bulat and Tzimiropoulos, 2017] proposed a heatmap loss to enforce structural consistency between the super-resolved and the corresponding HR facial image.

\[
l_{\text{heatmap}} = \frac{1}{N} \sum_{n=1}^{N} \sum_{i,j} (\tilde{M}_{i,j}^{n} - \bar{M}_{i,j}^{n})^2
\]  

where \( \tilde{M}_{i,j}^{n} \) is the heatmap corresponding to the \( n^{th} \) landmark at pixel \( (i,j) \) produced by running the FAN on the super-resolved image \( I^{HR} \), and \( \bar{M}_{i,j}^{n} \) is obtained by running another FAN on the original image \( I^{HR} \).
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Peak Signal to Ratio (PSNR)\textsuperscript{6}

**PSNR**

Given a reference image \(f\) and a test image \(g\), both of size \(M \times N\), the PSNR (in dB) between \(f\) and \(g\) is defined as

\[
PSNR = 10 \cdot \log_{10}(\frac{\text{MAX}_I^2}{MSE}) \tag{5}
\]

where

\[
MSE(f, g) = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (f_{i,j} - g_{i,j})^2 \tag{6}
\]

\(\text{MAX}_I\) is the maximum possible pixel value of the image. For example, when the pixels are represented using 8 bits per sample (grey-level), \(\text{MAX}_I = 255\).

A small value of the PSNR implies high numerical differences between images (not necessarily to be of low quality!).

\textsuperscript{6}[Hore and Ziou, 2010]
What’s wrong with the MSE?\(^7\)

\[\text{MSE}=0, \text{SSIM}=1\]
\[\text{CW-SSIM}=1\]

\[\text{MSE}=306, \text{SSIM}=0.928\]
\[\text{CW-SSIM}=0.938\]

\[\text{MSE}=309, \text{SSIM}=0.987\]
\[\text{CW-SSIM}=1.000\]

\[\text{MSE}=309, \text{SSIM}=0.576\]
\[\text{CW-SSIM}=0.814\]

\[\text{MSE}=313, \text{SSIM}=0.730\]
\[\text{CW-SSIM}=0.811\]

\[\text{MSE}=309, \text{SSIM}=0.580\]
\[\text{CW-SSIM}=0.633\]

\[\text{MSE}=308, \text{SSIM}=0.641\]
\[\text{CW-SSIM}=0.603\]

\[\text{MSE}=694, \text{SSIM}=0.505\]
\[\text{CW-SSIM}=0.925\]

\[\text{MSE}=871, \text{SSIM}=0.404\]
\[\text{CW-SSIM}=0.933\]

\[\text{MSE}=873, \text{SSIM}=0.399\]
\[\text{CW-SSIM}=0.933\]

\[\text{MSE}=590, \text{SSIM}=0.549\]
\[\text{CW-SSIM}=0.917\]

\[\text{MSE}=577, \text{SSIM}=0.551\]
\[\text{CW-SSIM}=0.916\]

\[\text{FIG2}\] Comparison of image fidelity measures for “Einstein” image altered with different types of distortions. (a) Reference image. (b) Mean contrast stretch. (c) Luminance shift. (d) Gaussian noise contamination. (e) Impulsive noise contamination. (f) JPEG compression. (g) Blurring. (h) Spatial scaling (zooming out). (i) Spatial shift (to the right). (j) Spatial shift (to the left). (k) Rotation (counter-clockwise). (l) Rotation (clockwise).

\[^7\text{[Wang and Bovik, 2009]}\]
[Wang et al., 2004] separates the task of similarity measurement into three comparisons:

- Luminance
- Contrast
- Structure
Fig. 3. Diagram of the structural similarity (SSIM) measurement system.
Luminance comparison function \( l(x, y) \)

\[
\mu_x = \frac{1}{N} \sum_{i=1}^{N} x_i
\]  

(7)

The luminance comparison function \( l(x, y) \) is a function of \( \mu_x \) and \( \mu_y \).

Contrast comparison \( c(x, y) \)

\[
\sigma_x = \left( \frac{1}{N - 1} \sum_{i=1}^{N} (x_i - \mu_x)^2 \right)^{1/2}
\]  

(8)

The contrast comparison \( c(x, y) \) is the comparison of \( \sigma_x \) and \( \sigma_y \).
The structure comparison $s(x, y)$ is conducted on these normalized signals.
These three components are combined to generate an overall similarity measure

\[ S(x, y) = f(l(x, y), c(x, y), s(x, y)) \]  

(11)

The general form of the Structural SIMilarity (SSIM) index between signal \( x \) and \( y \) is defined as

\[ SSIM(x, y) = [l(x, y)]^\alpha \cdot [c(x, y)]^\beta \cdot [s(x, y)]^\gamma \]  

(12)

Specifically, when \( \alpha = \beta = \gamma = 1 \), the resulting SSIM index is

\[ SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \]  

(13)

where \( C_1, C_2, \) and \( C_3 \) are small constants.

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\[ [\text{Wang et al., 2004, Wang and Bovik, 2009}] \]
Fig. 2. Comparison of “Boat” images with different types of distortions, all with MSE = 210. (a) Original image (8bits/pixel; cropped from 512×512 to 256×256 for visibility); (b) Contrast stretched image, MSSIM = 0.9168; (c) Mean-shifted image, MSSIM = 0.9900; (d) JPEG compressed image, MSSIM = 0.6949; (e) Blurred image, MSSIM = 0.7052; (f) Salt-pepper impulsive noise contaminated image, MSSIM = 0.7748.
Feature Similarity Index Measure (FSIM)\(^8\)

\[ \text{FSIM}_C = \frac{\sum \omega S_{PC}(x) \cdot S_{G}(x) \cdot \left[ S_{I}(x) \cdot S_{Q}(x) \right]^3 \cdot PC_m(x)}{\sum \omega PC_m(x)} \]

Fig. 2. Illustration for the FSIM/FSIM\(_C\) index computation. \(f_1\) is the reference image, and \(f_2\) is a distorted version of \(f_1\).

\(^8\)[Zhang et al., 2011]
Figure 1: **Which patch (left or right) is “closer” to the middle patch in these examples?** In each case, the traditional metrics (L2/PSNR, SSIM, FSIM) disagree with human judgments. But deep networks, even across architectures (Squeezenet [20], AlexNet [27], VGG [51]) and supervision type (supervised [46], self-supervised [13, 40, 42, 63], and even unsupervised [26]), provide an *emergent embedding* which agrees surprisingly well with humans. We further calibrate existing deep embeddings on a large-scale database of perceptual judgments; models and data can be found at https://www.github.com/richzhang/PerceptualSimilarity.

[Zhang et al., 2018]
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Figure 2: From left to right: bicubic interpolation, deep residual network optimized for MSE, deep residual generative adversarial network optimized for a loss more sensitive to human perception, original HR image. Corresponding PSNR and SSIM are shown in brackets. [4× upscaling]
Comparison of SRGAN and Super-FAN\textsuperscript{11}

Figure 1: A few examples of visual results produced by our system on real-world low resolution faces from WiderFace.

\textsuperscript{11}[Bulat and Tzimiropoulos, 2017]
Figure 4: Visual results on LS3D-W. Notice that: (a) The proposed Ours-pixel-feature already provides better results than those of SR-GAN [20]. (b) By additionally adding the newly proposed heatmap loss (Ours-pixel-feature-heatmap) the generated faces are better structured and look far more realistic. Ours-pixel-feature-heatmap-GAN is Super-FAN which improves upon Ours-pixel-feature-heatmap by adding the GAN loss and by end-to-end training. Best viewed in electronic format.
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Challenges: from toy data to real-world problems

- Computation Efficiency
- Robustness
- Real-world Performance
- And more . . .

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\[12^\text{Higher MSE does not have to be visually more appealing! Bicubic interpolation usually achieves smaller MSE compared with those recovered by some example-based approaches [Yang et al., 2010].}\]

\[13^\text{[Huang and Yang, 2010]}\]
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