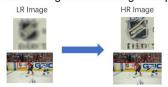
Multi-Reference Image Super-Resolution: A Posterior Fusion Approach

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Motivation

Single-Image Super-Resolution (SISR)

- · Recover the high-resolution version of a image
- · III-posed inverse problem with infinite solutions
- · No universal regularization to guide optimization



Single-Reference-based Super-Resolution (SRefSR)

- High-resolution reference provides additional information for texture restoration
- · Only one reference supported



Our Goal

- · Utilize information from multiple references
- Should be easily integrated into any SRefSR pipeline to improve performance
- Low computational cost

Potential Applications: Video game scenes

- NVIDIA DLSS: Train separate SR neural networks for each video game
- · Multiple HR texture patches readily available
- Could use single model for any video game, and save huge amount of computing resources

Related Work

SISR models

Convolutional Neural Networks

- SRCNN [1], EDSR [2]
- Smooth reconstruction

Generative Adversarial Networks

- SRGAN [3]
- · Generate "fake" texture details
- Texture details different from ground-truth

SRefSR models

Convolutional Neural Networks

- CrossNet [4]
- Align reference and LR features
- Not specify suitable references (by similarity)

Similarity-Aware Deformable Convolution

- SSEN [5]
- · Detect relevancy of reference
- · More robust with irrelevant references
- · Performance still relies on reference choice

Dual zoomed observations with self-supervision

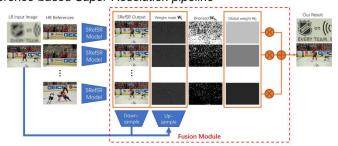
- · SelfDZSR [6]
- Telephoto as references

References

[1] C. Dong et al., "Image super-resolution using deep convolutional networks," CoRR, vol. abs/1501.00092, 2015. [2] B. Lim et al., "Enhanced deep residual networks for single image super-resolution," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, July 2017. [3] C. Ledg et al., "Photo-realistic single image super-resolution using a generative adversarial network," in Proceeding of the IEEE conference on computer vision and pattern recognition, 2017, pp. 4681–4690. [4] H. Zheng et al., "Crossnet: An end-to-end reference-based super-resolution network using cross-scale warping," in Proceedings of the European Conference on Computer Vision (ECCV), September 2018. [5] G. Shim et al., "Robust reference-based super-resolution with similarity-wave deformable convolution," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020. [6] Z. Zhang et al., "Sef-supervised learning for real-world super-resolution from dual zoomed observations," arXiv preprint arXiv:2203.01325, 2022.

New Technique

Multi-Reference-based Super-Resolution pipeline



Part 1: Single-Reference-based Super-Resolution (SRefSR) Module

- · Align input and reference image spatially and semantically
- One LR image + Multiple HR reference images → Multiple SRefSR outputs

Part 2: Image Fusion Module

- · Goal: Combine the best regions of each SRefSR output
- Step 1: Adaptive Weight Masking

$$W_i = U\left(\exp\left(-\beta \left(\mathcal{D}(I_i) - I_{input}\right)^2\right)\right) \qquad \hat{I}(p) = \frac{1}{\sum_{l=1}^N W_i(p)} \sum_{l=1}^N I_i(p) W_i(p)$$
(The idea: higher weights for matching regions)

Step 2: Globally Reference-Quality-based Weighted Averaging

$$W_{b_i}(p) = \begin{cases} 1 \ if \ i = argmax_i \ W_i(p) \\ 0 \ otherwise \end{cases} \quad w_i = \exp \left(\beta_g \sum_p W_{b_i}(p)\right) \quad I_{fused} = \frac{1}{\sum_i w_i} \sum_i w_i \hat{I}_i$$

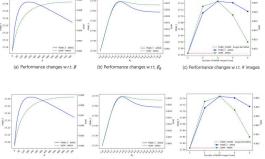
(The idea: higher overall weights for high-quality SRefSR output)

Experimental Results

Qualitative Comparison

Input Image	HR	C ² - Matching	AMSA	Input Image	HR	C ² - Matching	AMSA
Reference Image	ESRGAN	Ours (C ² - Matching)	Ours (AMSA)	Reference Image	ESRGAN	Ours (C ² - Matching)	Ours (AMSA)
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Quantitative Evaluations



- When β , $\beta_g=0$: Naive Fusion
- 1st & 2nd col: PSNR_Y/SSIM rise as $\beta \& \beta_g$ increase, showing distorted regions are penalized
- 3rd col: RefSR images with less and less quality are fused, showing the fusion method is resistant to low-quality inputs.
- 1st & 2nd row: The proposed method is tested on two RefSR models, showing consistent performance improvement