# SRHRF+: Self-Example Enhanced Single Image Super-Resolution Using Hierarchical Random Forests



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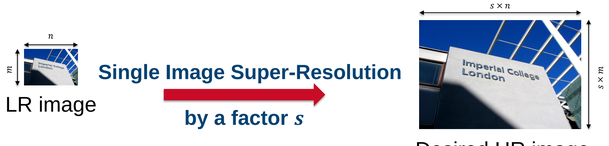
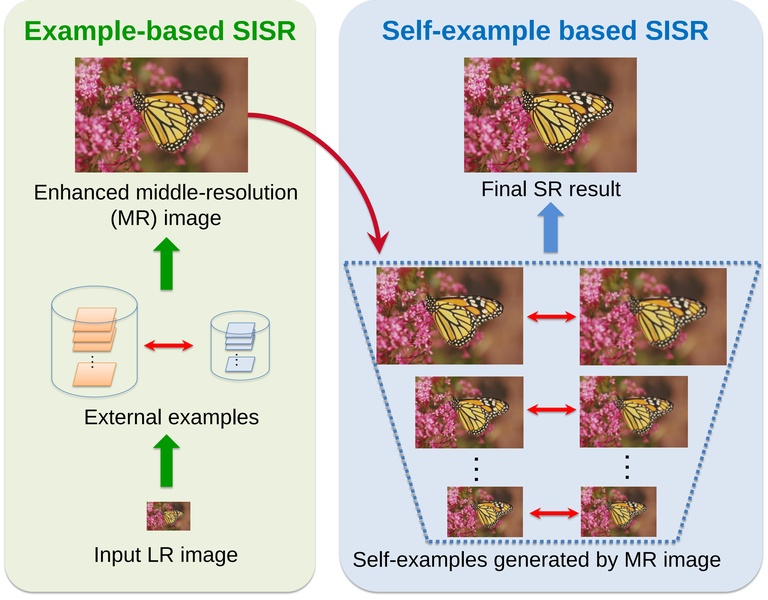
## Introduction and Motivation

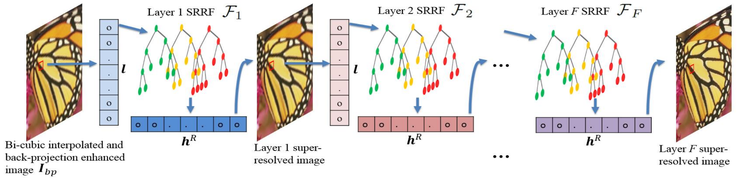
- Can we overcome the limitation of a camera and, given the pixels, obtain a sharper image with increased resolution?



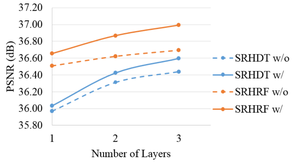

- Proposed to combine the stability of **Example-based SISR** and the adaptability of **Self-example based SISR**:




## SR via Hierarchical Random Forests

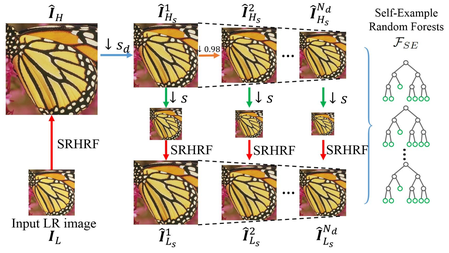


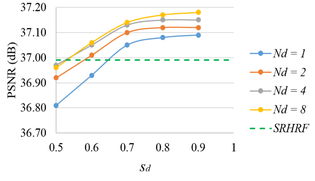

- Learning LR-HR patch correspondences with **a hierarchical random forests** (SRHRF).
- **Regression model fusion** applied in random forests at each stage leading to 8 times more decision trees in a forest.
- **Hierarchical structure** further boosts performance.




## Self-Example Random Forests

- Exploit non-local self-similar patterns using random forests.
- SRHRF generates a high quality middle-resolution (MR) image.
- The MR image is rescaled by **a factor $s_d$** ($> 1/s$) to construct an image pyramid pair $\{\hat{I}^i_{H_s}, \hat{I}^i_{L_s}\}_{i=1}^{N_d}$ for self-example learning.
  - Faithful similar structure, especially for large upscaling factor.
  - Sufficient number of training samples.




The MR image can be rescaled by a factor larger than $1/s$ to generate the self-example image pyramid

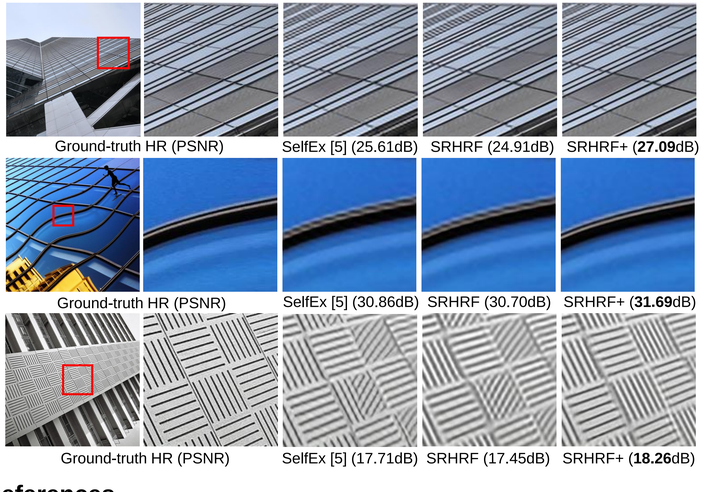
## Numerical Results

- Objective comparisons:

| | | | Bicubic | A+ [ 1 ] | RFL [ 2 ] | SRHDT [ 3 ] | SRCNN [4] | SelfEx [5] | SRHRF | SRHRF+ |
|---|---|---|---|---|---|---|---|---|---|---|
| Set5 | ×2 | PSNR | 33.66 | 36.54 | 36.54 | 36.92 | 36.66 | 36.49 | 37.19 | **37.29** |
| | | SSIM | 0.9299 | 0.9544 | 0.9537 | 0.9546 | 0.9542 | 0.9537 | 0.9568 | **0.9574** |
| | ×4 | PSNR | 28.42 | 30.28 | 30.14 | - | 30.48 | 30.31 | 30.74 | **30.82** |
| | | SSIM | 0.8104 | 0.8603 | 0.8548 | - | 0.8628 | 0.8619 | 0.8706 | **0.8710** |
| Set14 | ×2 | PSNR | 30.24 | 32.28 | 32.26 | 32.67 | 32.42 | 32.22 | 32.85 | **32.91** |
| | | SSIM | 0.8683 | 0.9056 | 0.9040 | 0.9069 | 0.9063 | 0.9034 | 0.9097 | **0.9104** |
| | ×4 | PSNR | 26.00 | 27.32 | 27.24 | - | 27.49 | 27.40 | 27.69 | **27.74** |
| | | SSIM | 0.7027 | 0.7491 | 0.7451 | - | 0.7503 | 0.7518 | 0.7574 | **0.7582** |
| Urban100 | ×2 | PSNR | 26.86 | 29.20 | 29.11 | 29.75 | 29.50 | 29.54 | 30.13 | **30.77** |
| | | SSIM | 0.8395 | 0.8938 | 0.8904 | 0.8985 | 0.8946 | 0.8967 | 0.9038 | **0.9110** |
| | ×4 | PSNR | 23.14 | 24.32 | 24.19 | - | 24.52 | 24.79 | 24.70 | **25.10** |
| | | SSIM | 0.6577 | 0.7183 | 0.7096 | - | 0.7221 | 0.7374 | 0.7305 | **0.7422** |

Table 1: PSNR (dB) and SSIM of different SISR methods on *Set5*, *Set14* and *Urban100* with upscaling factor 2 and 4.

- Subjective comparisons:




## References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[3] J.-J. Huang and W.-C. Siu. Learning hierarchical decision trees for single image super-resolution. IEEE Trans. on Circ. and Sys. Video Tech., 2016.
[4] C. Dong, C. C. Loy, K. He, and X. Tang. Learning a deep convolutional network for image super-resolution. ECCV, pages 184–199, 2014.
[5] J.-B. Huang, A. Singh, and N. Ahuja. Single image superresolution from transformed self-exemplars. CVPR, pages 5197–5206, 2015.