



Enhancing and Revealing Hidden Image Details

Madeline Hays

Department of Bioengineering, Stanford University

1 Motivation

To see more in an image.
Forensic experts often rely on low-quality and widely varying surveillance sources to capture images of vehicles and subjects. Images face many sources of corruption:

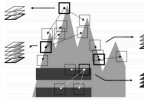
· Read Noise · Motion Blur · Poor Exposure · Low Resolution ·

The goal is to compile an image enhancement tool set to reveal image details while avoiding hallucinated artifacts.

2 Related Work

Techniques target single corruption source.

Read Noise



To denoise gaussian corruption of images, Dabov *et al.* groups similar 3D patches in images and thresholds the patches in the discrete cosine transform domain to filter noise.

Motion Blur

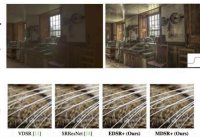
Weiner and RL deconvolution mitigate motion blur with known blur kernels; Krishnan *et al.* estimate unknown kernels via normalized sparsity measure.

Poor Exposure

Paris *et al.* normalize or enhance images using edge-aware Laplacian pyramids.

Low Resolution

Lim *et al.* super-resolve images via residual dCNNs.



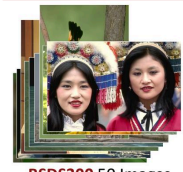
5 References

· K. Dabov, A. Foi, V. Katkovnik, K. Egiazarian, "Image Denoising by Sparse 3D Transform-Domain Collaborative Filtering," IEEE Transactions on Image Processing, vol. 16, no. 8, pp. 2080-2095, 2007.
· D. Krishnan, T. Tay, R. Fergus, "Blind Deconvolution Using a Normalized Sparsity Measure," IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2011.
· S. Paris, S. Hasiuff, J. Kautz, "Local Laplacian Filters: Edge-Aware Image Processing with a Laplacian Pyramid," ACM Transactions on Graphics (TOG), Proceedings of SIGGRAPH, 2011.
· B. Lim, S. Son, H. Kim, S. Nah, K. M. Lee, "Enhanced Deep Residual Networks for Single Image Super-Resolution," Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, 2017.

3 Methods

Evaluate image enhancement techniques on the different image corruption types and formulate pipeline.

1. Image Selection



BSDS300 50 Images

2. Noising



Motion Blur

Gaussian Noise

Poor Exposure

Low Resolution

$$I_{blurred}(x,y) = (I * K)(x,y)$$

$$K(u,v) = \frac{1}{N} \begin{bmatrix} 1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 1 \end{bmatrix}, \quad N = \text{size}(K)$$

$$I_{noisy}(x,y) = I(x,y) + N(x,y)$$

$$N(x,y) \sim N(0, \sigma)$$

$$I_{exp}(x,y) = f \cdot I(x,y)$$

$$\text{Underexposure: } 0 < f < 1$$

$$\text{Overexposure: } f > 1$$

$$I_{lowpass}(x,y) = \sum_{u=-k}^k \sum_{v=-k}^k I(x-u, y-v) G(u,v, \sigma)$$

$$I_{down}(x',y') = I_{lowpass}(sx', sy')$$

$$G(u,v, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}, \quad \sigma = \frac{s}{2}$$

$$s = \text{scale}, \quad k = \text{radius}$$

Classify Noise via peak intensity, contrast, standard deviation, transform variance, and per pixel FOV area.

3. Denoising / Enhancement

Deconvolution



Filtering



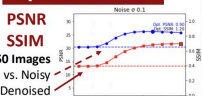
Tone Mapping



Sharpening



4. Evaluation



4 Results

Compiling tool set for images with multiple sources of corruption.



PSNR = 11.07 dB
SSIM = 0.19

1. Exposure Correction



PSNR = 14.27 dB
SSIM = 0.20

2. Noise Filter



PSNR = 16.20 dB
SSIM = 0.44

3. Deblur



PSNR = 16.22 dB
SSIM = 0.44

4. Tone Mapping



PSNR = 16.23 dB
SSIM = 0.44

5. Sharpening



PSNR = 16.26 dB
SSIM = 0.44

Denoising strategies are highly effective against their targeted corruption type but can inadvertently degrade image quality when applied to non-targeted distortions. In images with multiple corruption sources, assessing noise characteristics is essential for designing an optimal recovery pipeline with properly ordered stages and tunable parameters.