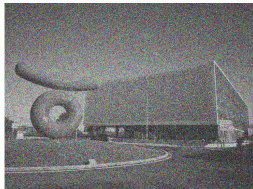


Image denoising with multi-layer perceptrons

ESTEVE Nathan
FATTOUHY Mohamed
NGUYEN Louis
VERNAY Amélie
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Clean image



Noisy image

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Image denoising with multi-layer perceptrons, part 1: comparison with existing algorithms and with bounds, H. C. Burger, C. J. Schuler, S. Harmeling (2012)

Image denoising

Image denoising seeks to find a clean image given only its noisy version.

Trade-off

Image denoising requires to denoise patches separately:

- very small patches lead to a function that is easily modeled, but to bad denoising results;
- very large patches potentially lead to better denoising results, but the function might be difficult to model.

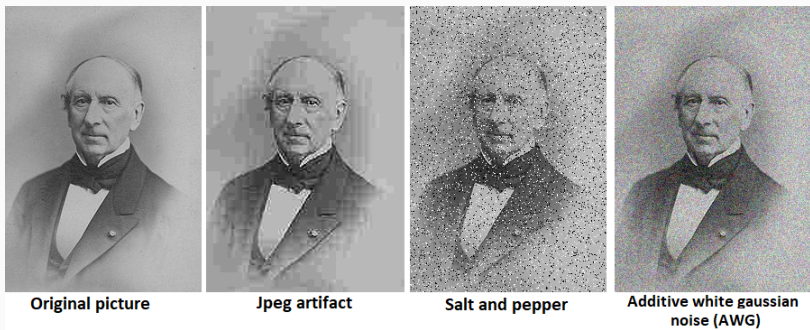
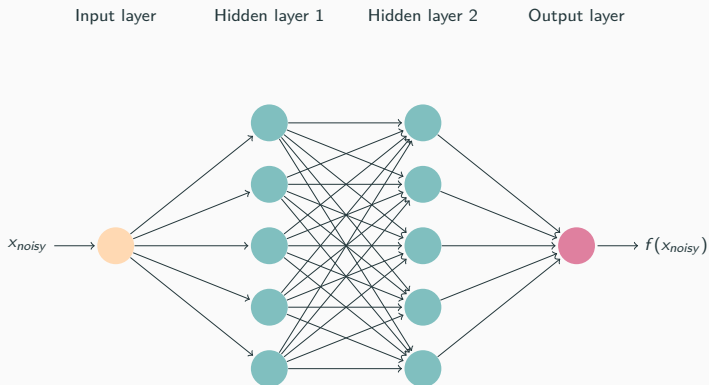


Figure 1: Image of Louis Augustin Cauchy with differents noises

MLP-based method

A multi-layer perceptron is a fully connected neural network.



x_{noisy} is a noisy version of a clean patch x ; $f(x_{noisy})$ represents an estimate of x .

Weight initialization for MLP-based method

Weights w are sampled from an uniform distribution :

$$w \sim U \left[-\frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}, \frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}} \right]$$

n_j and n_{j+1} are the number of neurons in the input and output sides of the layer.

Loss function

The loss function used is the MSE :

$$MSE = \frac{1}{n} \sum_{i=1}^n (f(x_i) - x_i)^2,$$

where $f(x)$ the estimation x and x is a clean patch.

Peak Signal-To-Noise Ratio (PSNR)

$PSNR = 20 \times \log_{10} \left(\frac{m}{\sqrt{MSE}} \right)$ (dB), where m is the maximum possible pixel value of a given image.

image	KSVD	EPLL	BM3D	NLSC	MLP
Barbara	29.49dB	28.52dB	30.67dB	<i>30.50dB</i>	29.52dB
Boat	29.24dB	29.64dB	29.86dB	<i>29.86dB</i>	29.95dB
C.man	28.64dB	29.18dB	29.40dB	<i>29.46dB</i>	29.60dB
Couple	28.87dB	29.45dB	<i>29.68dB</i>	29.63dB	29.75dB
F.print	27.24dB	27.11dB	27.72dB	27.63dB	<i>27.67dB</i>
Hill	29.20dB	29.57dB	<i>29.81dB</i>	29.80dB	29.84dB
House	32.08dB	32.07dB	<i>32.92dB</i>	33.08dB	32.52dB
Lena	31.30dB	31.59dB	<i>32.04dB</i>	31.87dB	32.28dB
Man	29.08dB	29.58dB	29.58dB	<i>29.62dB</i>	29.85dB
Montage	30.91dB	31.18dB	32.24dB	<i>32.15dB</i>	31.97dB
Peppers	29.69dB	30.08dB	30.18dB	30.27dB	30.27dB

Table 1: Results on 11 standard test images for $\sigma = 25$.



clean image (198054)



BM3D: 26.28dB



MLP: 27.09dB

Figure 2: BM3D and MLP performances (AWG noise $\sigma = 25$)



Figure 3: MLP and BM3D performances on strip noise



s & p noise: 12.41dB



median filtering: 30.33dB



MLP: 35.08dB

Figure 4: MLP and median filtering performances on salt and pepper noise



Figure 5: MLP and median filtering performances on JPEG Artifact

Clustering-based bounds

There exist inherent limits on denoising quality for images with rich geometric structure.

Bayesian framework

Bayesian bounds estimate how well any denoising algorithm can perform in a bayesian framework which depends on the patch size.

Block-matching

We look for the patches most similar to a reference patch.

Combine MLP and block-matching

We train MLPs that take as input a reference patch and its nearest neighbors (similar patches).

Results

Block-matching MLPs provide better results on images with repeating structure than plain MLPs.

However, BM3D and NLSC still provide better results on this kind of images.

- Excellent results BUT outperformed by BM3D and NLSC on images with a lot a regular structure;
- The MLP-based approach achieves excellent results, no matter the type of noise, especially with high levels of noise.
- The MLP-based approach shows that it is possible to significantly improve denoising quality on images with complex textures.
- Is it possible to find an approach that would perform state-of-the-art results on every image ?