

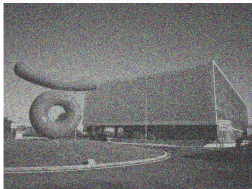
# Image denoising with multi-layer perceptrons

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October 19, 2021



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)

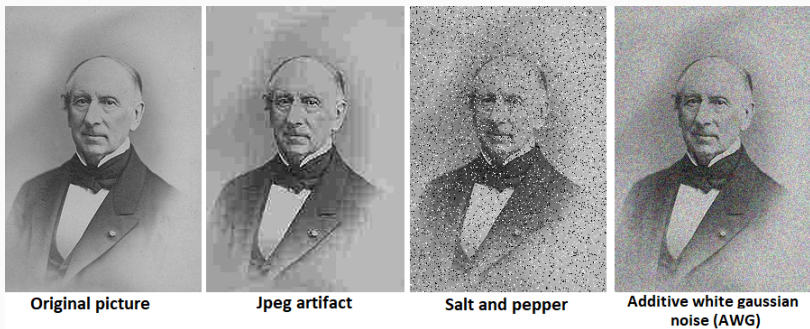
## Image denoising

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

## Trade-off

Image denoising requires to denoise patches separately:

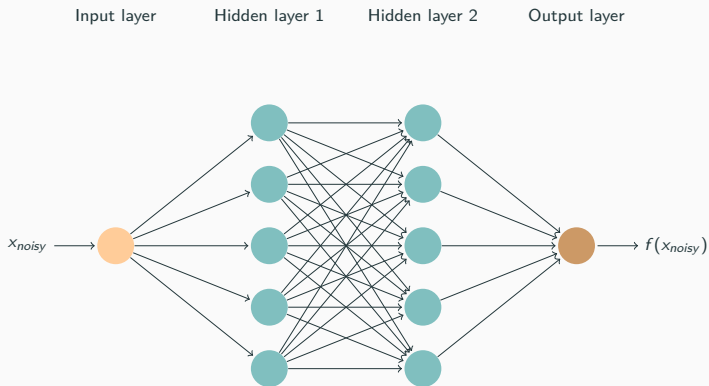
- very small patches lead to a function that is easily modeled, but to bad denoising results;
- very large patches potentially lead to better denoising results, but the function might be difficult to model.



**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 :

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

where  $x_{clean}$  is a clean patch and  $f(x_{noisy})$  the estimation of  $x_{clean}$ .

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

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  $\sigma = 25$ )



## 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.



**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 SA-DCT performances on JPEG Artifact

## 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.
- Would it be possible to find an approach that would perform state-of-the-art results on every image ?