Image denoising with multi-layer perceptrons

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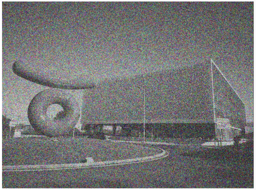
Clean image



Noisy image

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Context

***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.

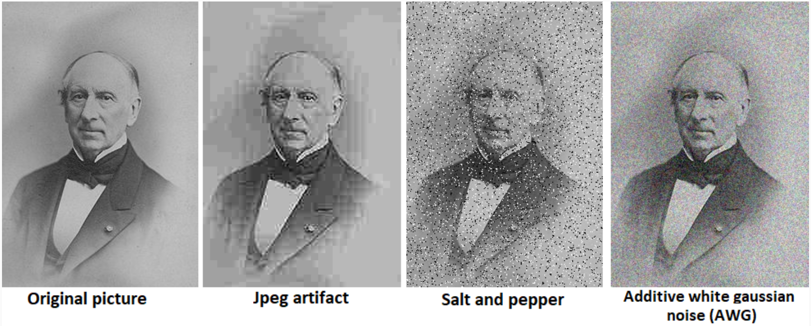
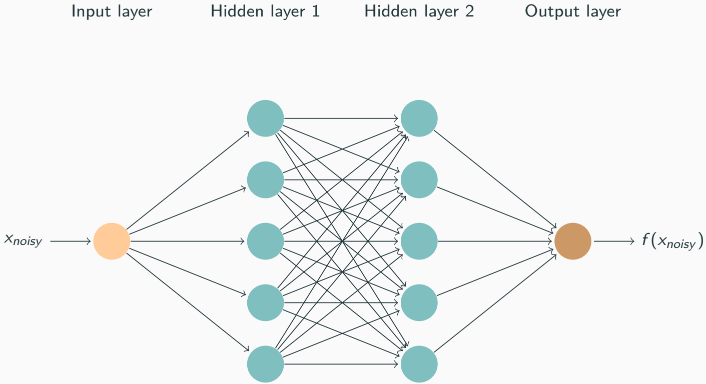


Figure 1: Image of Louis Augustin Cauchy with differents noises

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 :

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

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

Peak Signal-To-Noise Ratio (PSNR)

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

Results for AWG noise

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

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

Results for AWG noise

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

Bounds

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.

Other types of noise

Figure 3: MLP and BM3D performances on strip noise

Other types of noise

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

Other types of noise

Figure 5: MLP and median filtering 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.

Conclusion

- 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 ?