

Image Denoising - Homework 1 Report

MVA 2021-2022

ENS Paris-Saclay

Nicolás Violante

nviolante96@gmail.com

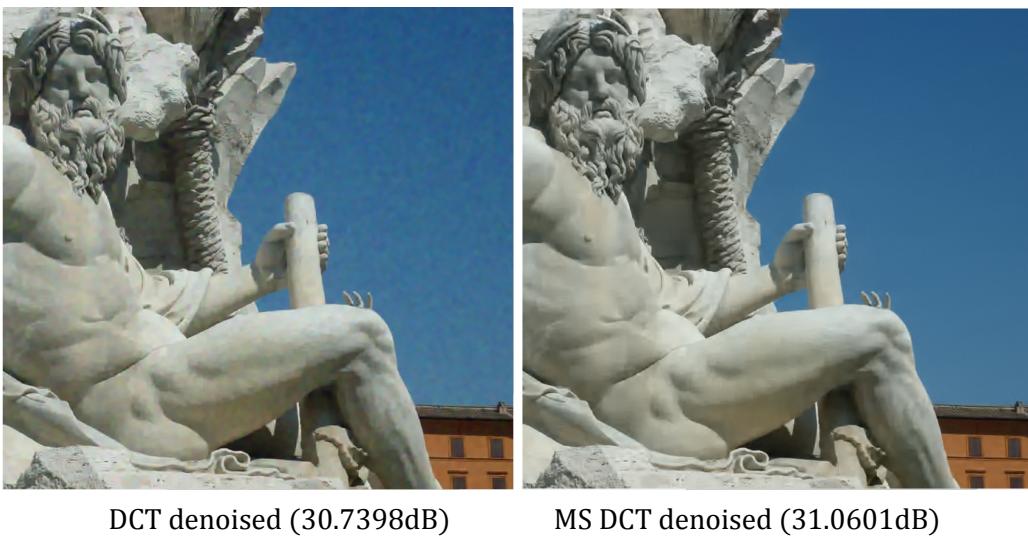
In this brief analysis of some DCT-based denoising methods, we look at some particular details of the denoised images such as flat areas and edges.

Multi-Scale DCT Denoising



Original

Noisy (18.7689dB)



DCT denoised (30.7398dB)

MS DCT denoised (31.0601dB)

Figure 1: General comparison between DCT denoising and MS DCT denoising with additive noise with $\sigma=30$ using DCT size = 8, 5 scales, and freq=0.4.

From Figure 1 is clear that MS DCT outperforms the denoising performance of DCT. The difference is not only visual but is also supported by the PSNR, where MS DCT gets an extra 0.3203dB. The most distinctive feature between both denoised images is in the sky

regions, where the results obtained with MS DCT are spectacularly better. Despite the good denoising results, it is noticeable that both denoised images lose some high-frequency details. This can be seen in the leg of the statue.

Effect of adaptive aggregation

As claimed in the MS DCT paper, using adaptive aggregation plays a fundamental role in removing artifacts in zones with edges. The following example, Figure 2, illustrates the performance boost obtained. When adaptive aggregation is not used, ringing artifacts appear between the statue and the sky.

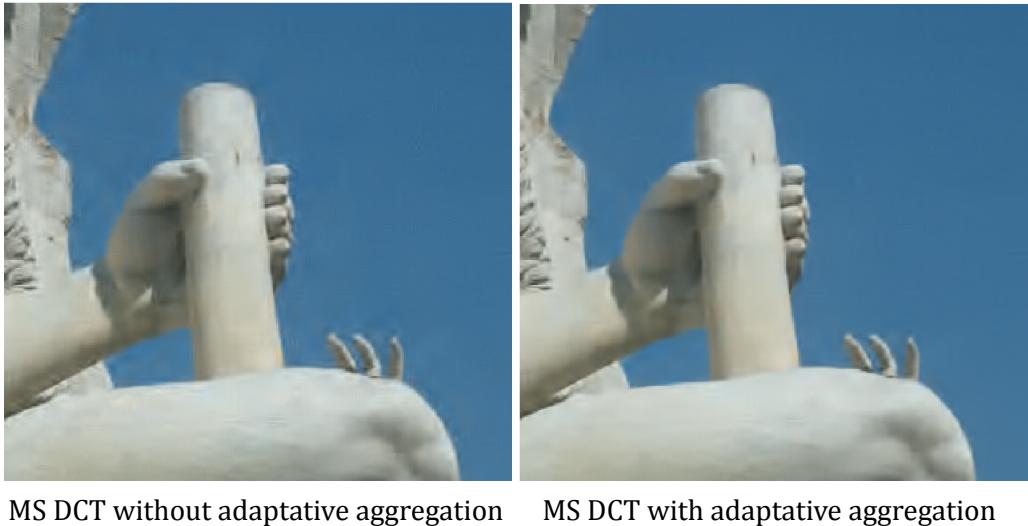


Figure 2: Comparison for MS DCT denoising for noise with $\sigma=30$.

Effect of DCT size

Using smaller sizes for the DCT may lead to undesirable effects all over the image. For example in Figure 3, a noisy pattern is observed all across the denoised image.

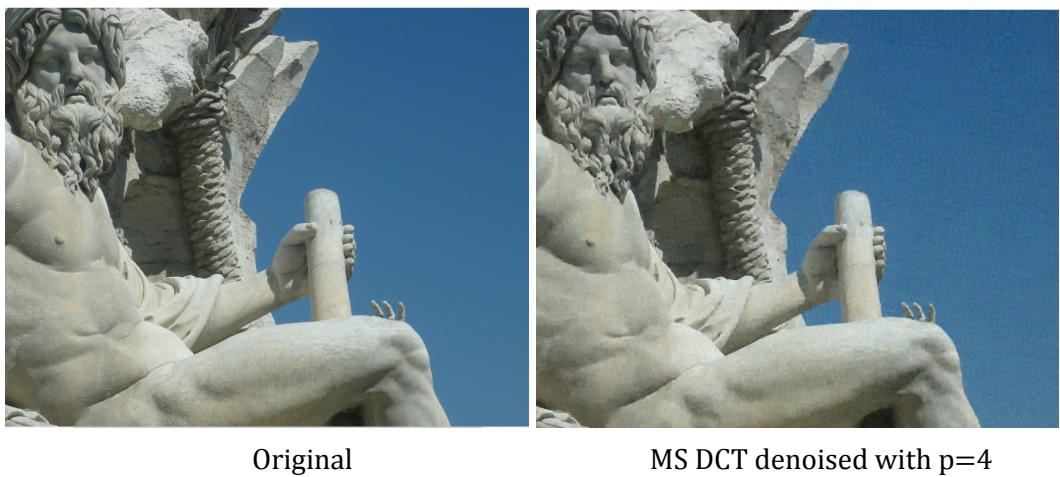


Figure 3: Comparison for MS DCT denoising with $\sigma=30$, DCT size = 4, 5 scales, and freq=0.4.

In addition, using patches bigger than 8, for example, 16, doesn't result in a noticeable performance increment. Therefore, taking 8 as default seems like a reasonable choice.

Effect of noise variance

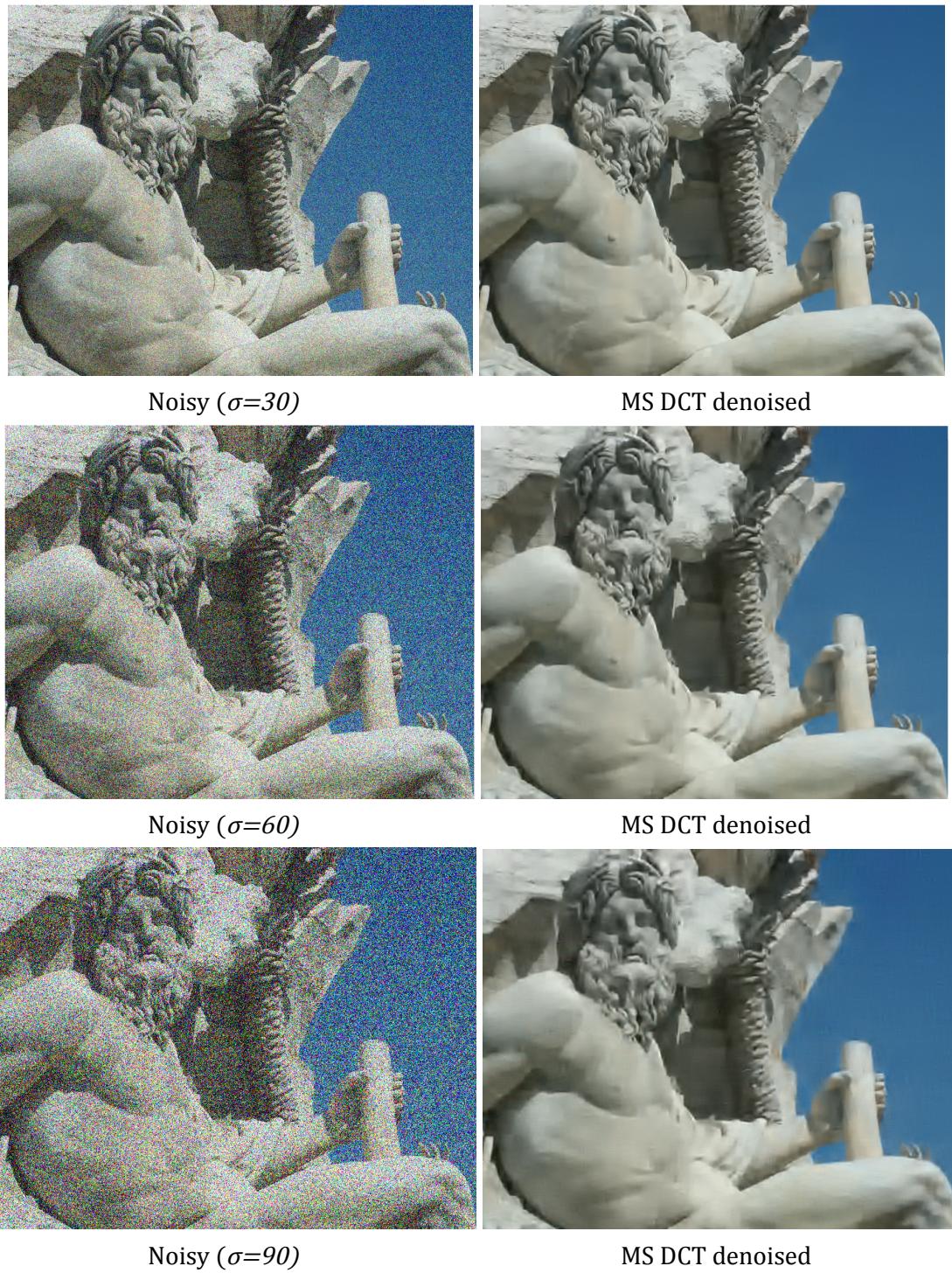
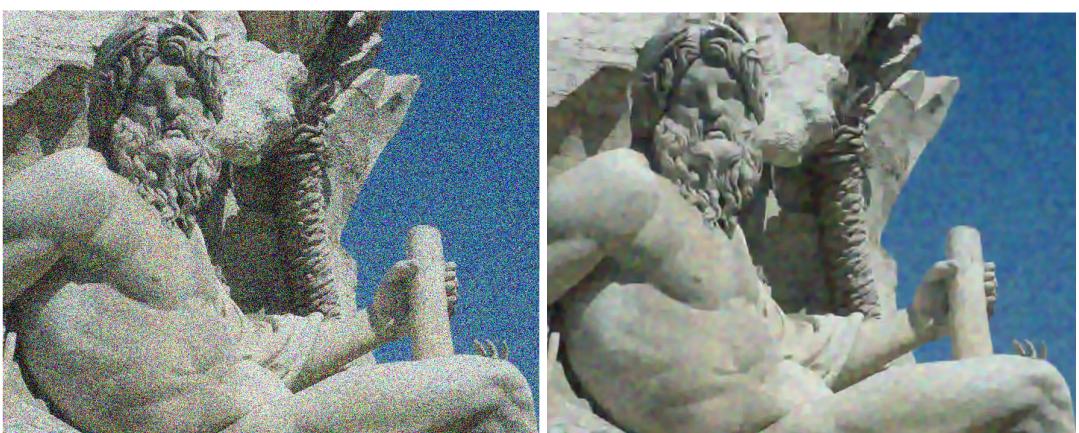


Figure 4: Comparison for MS DCT denoising with DCT size = 8, 5 scales, and freq=0.4 for noise variance $\sigma=30$, $\sigma=60$, and $\sigma=90$.



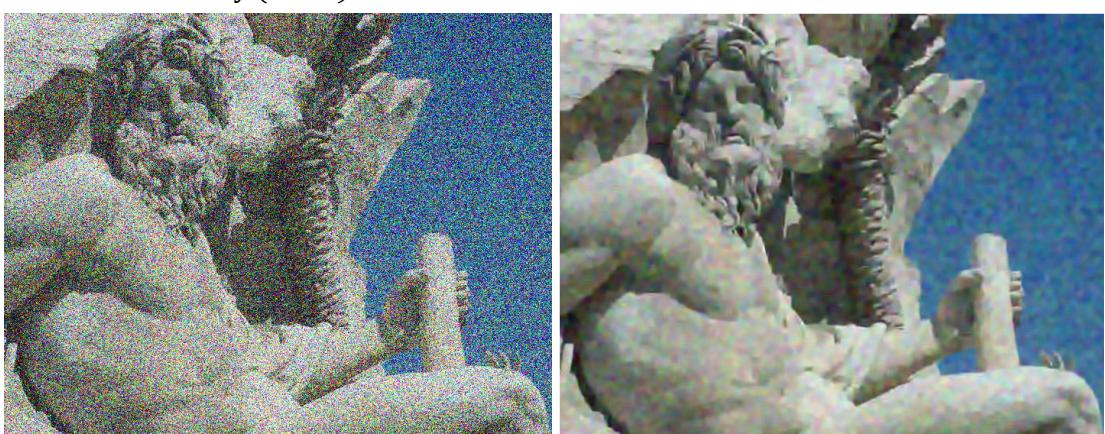
Noisy ($\sigma=30$)

DCT denoised



Noisy ($\sigma=60$)

DCT denoised



Noisy ($\sigma=90$)

DCT denoised

Figure 5: Comparison for DCT denoising with DCT size = 8 for noise variance $\sigma=30$, $\sigma=60$, and $\sigma=90$.

We tried MS DCT denoising for three values of noise: $\sigma=30$, $\sigma=60$, and $\sigma=90$. Results are shown in Figure 4. This method achieves remarkable results, even for the highest values of noise. Even though some details in the statue's texture are lost, the reconstruction is incredibly good if we take into account the amount of noise present in the input image. Moreover, the sky regions are very smooth, and only in the $\sigma=90$ case, some small artifacts are presented.

This is a huge difference in performance compared with DCT denoising, as seen in Figure 5. In this case, the noisier is the input image, the worst performance is achieved after denoising. There are visible artifacts all over the image and the sky regions don't look good at all.

Conclusions

The following is a summary of the most important observations from the previous experiments:

- MS DCT outperforms DCT in general but especially in flat regions of the image where the results are smoother. Using multiple scales drastically improves denoising.
- In both cases, it is noticeable that some high-frequency details are lost.
- Adaptive aggregation on MS DCT helps to remove undesired artifacts near the edges.
- The patch size of the DCT plays a fundamental role in the final results. Setting a value too low may cause artifacts all over the image.
- Unlike DCT, MS DCT achieves great results even with really big values of noise.

Estimating a noise curve from a single image

The authors propose a procedure to estimate the noise σ in an image. It consists in taking M overlapping blocks from the image and computing the DCT of each one of them. Then each DCT coefficient from every block is labeled as low or high frequency. After that, the procedure is as following:

- Compute the variance associated with the low frequency of all the blocks
- Compute the variance associated with the high frequency of the K blocks with smaller low-frequency variance.

The justification for this step is that blocks with small low-frequency variance are likely to be homogeneous regions where the high-frequency variance corresponds to the noise. Finally, the overall noise estimation is given by the median of the K variances associated with the high frequency.

Moreover, the authors argue that in reality, it is not accurate to assume a uniform σ for all pixels of the image, in particular, because the AWGN model is not valid for dark areas. Therefore they extend their method and compute an estimate for each intensity based on the histogram of the block's means. For each block on the image, they compute the mean and classify the blocks according to the bin that contains its mean. Then they apply the already presented algorithm on the blocks that belong to each bin, thus obtaining a noise estimate for each intensity.



Noisy image

Figure 6: Raw image (noisy) used to test the noise estimator procedure.

To test the coherence of the estimation a down-scaling procedure is done by taking the average of 4×4 blocks. Then, if each pixel is modeled as an independent random variable with identical standard deviation σ (we can assume this since they are close pixels) the standard deviation of the average is $\sigma/2$. Therefore, we can check the coherence of the noise estimation algorithm by down-scaling the image, estimating the noise, and checking that it is approximately half of the upper scale.

From the results of Figure 7 is clear that at each scale the noise estimator is reduced by a factor of two. We also note that at each scale there are fewer mean values at which noise is estimated due to the average down-scaling.

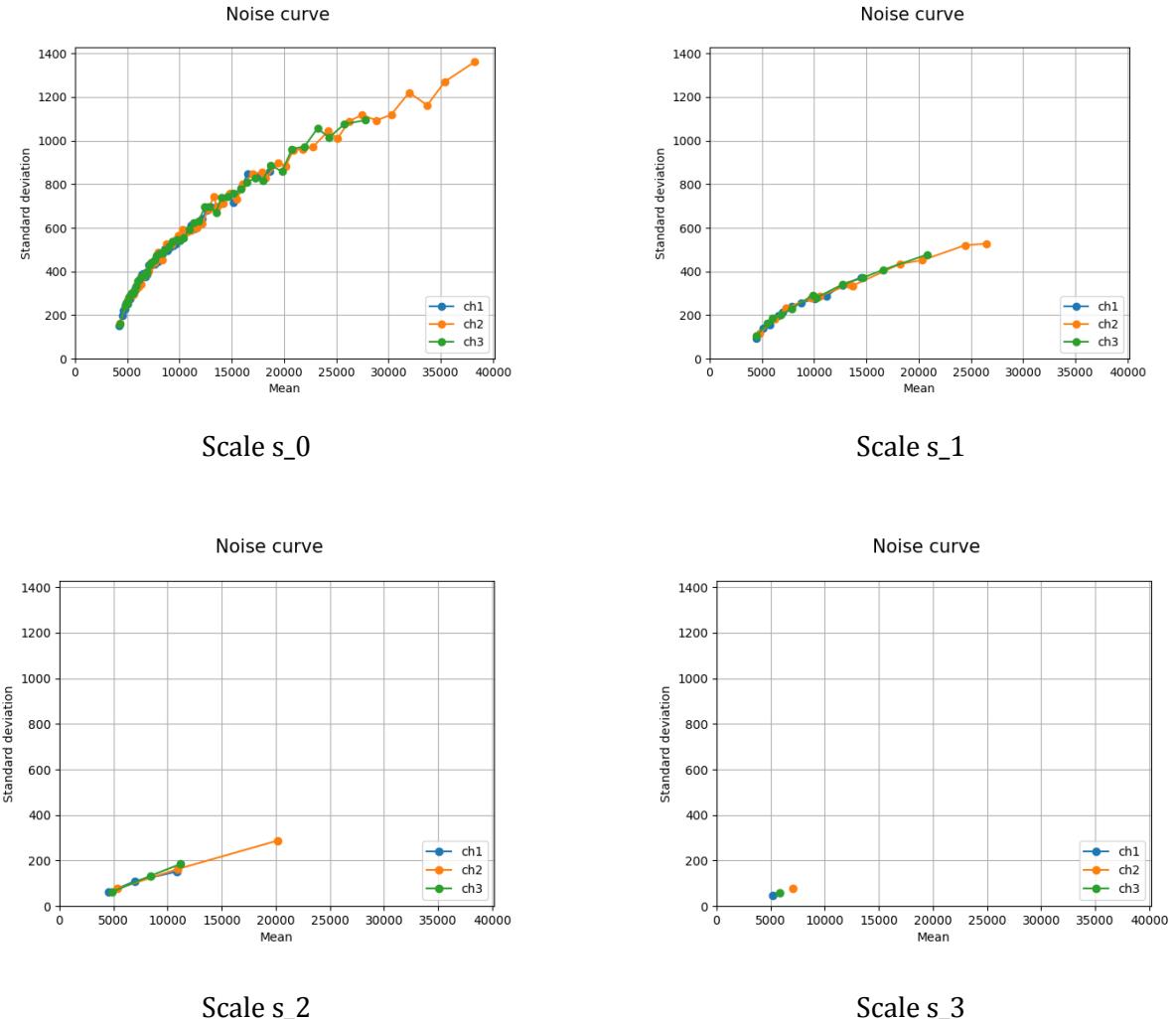


Figure 7: Noise curves for the image of Figure 6 at different scales.