Image denoising: cours 2

Experimental report

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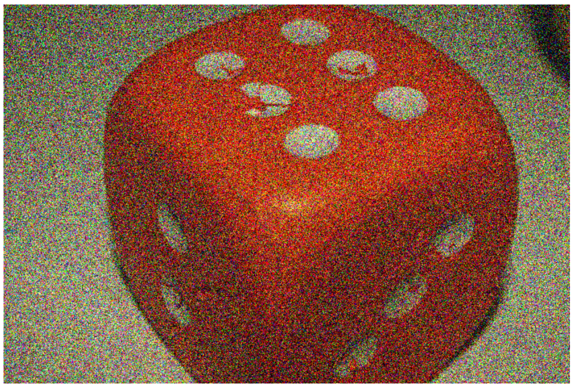
Experiments with 3 denoising algorithms: Non-Local Means Denoising, Multi-Scale DCT Denoising and BM3D

Before going to the experiments I find relevant to note that NLM and MS-DCT work under really different ideas, the first one is a self-similarity method, and the second one a method that looks for sparse representations on the frequency domain. It’s for that reason that one can expect one method to be better than the other depending on the context. As we’ll be able to observe shortly, in a context of few edges and big areas of self-similar patches, NLM will have the best results without introducing artifacts, on the other hand, in areas full of details and edges, frequency methods can be better at preserving details, but can also introduce some artifacts.
Finally, BM3D can be understood as a method that joins and extends both previous algorithms into a single one, having the best of both worlds.

Regular image with few details and edges and high noise

Original image



Noisy image (std = 75)

MS-DCT(33.4614)

BM3D(32.7472)

NLM(31.96)

In the above image, I think that the worst performance (perceptually) is the one by BM3D. It can be seen that it introduces some ugly artifacts in the regular areas of the background. I understand that those artifacts can be mainly related to manipulations on the frequency domain, and are similar to the ones observed under single scale DCT (related to residual low frequency noise). On the other hand, MS-DCT seems to address that issue and returns a good image, with less of those patterns.
NLM being a relatively uniform image performs quite well, although due to the averaging nature of the algorithm, some details got erased (marks in the "3" face of the dice). However, I find NLM to return the best result on this experiment.

More complex image with different regions and moderate noise

Original

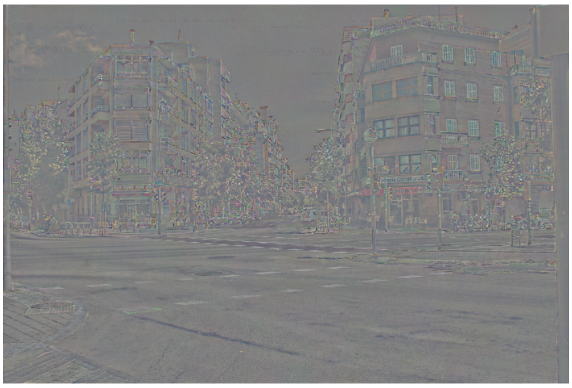
Noisy image (std=30)

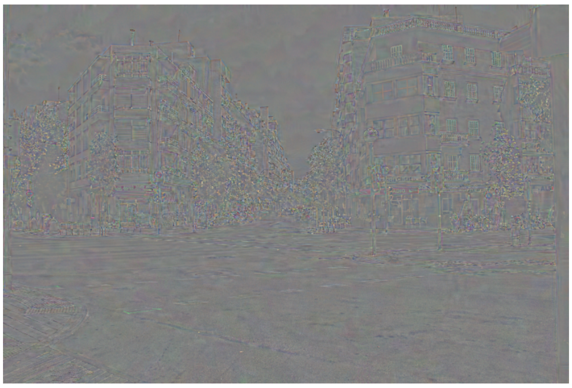
MS-DCT(30.2505)

BM3D(30.6928)

NLM(29.26)

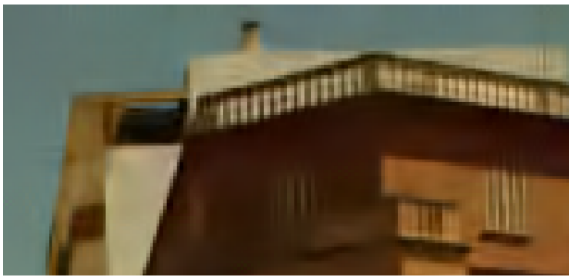
In this experiment, with an image with lots of details, the best results are obtained by MS-DCT and BM3D. NLM erases lots of fine details, such as some patterns on the street and the sidewalk.





Difference between denoised and original images. NLM on the left and BM3D on the right.

BM3D produced remarkably good results in this image, preserving lots of the details while removing a great amount of noise without adding strange artifacts. One comparison of the performance in preserving fine details can be observed by looking at the top floor balcony on the building on the right. BM3D is the algorithm which preserves more details than the rest.



MS-DCT

BM3D

NLM

Original

More experiments with NLM

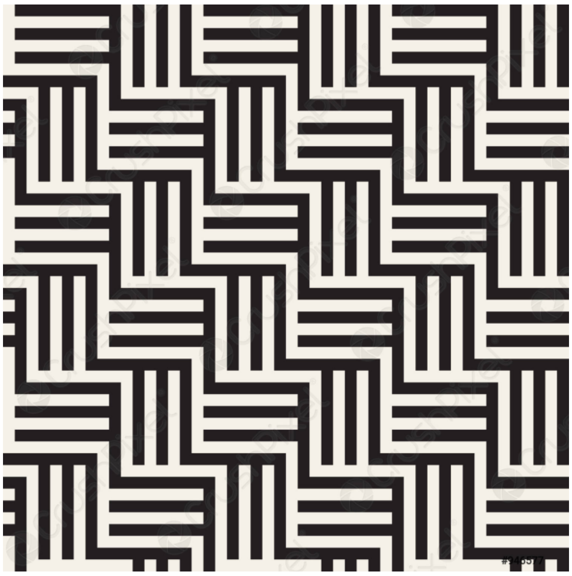
In the previous homework I already read the MS-DCT paper and did some experiments, especially focusing on the adaptive aggregation details. For this homework I carefully read Non-Local Means Denoising and reviewed the course notes and slides for BM3D. In this section I'm going to show some more experiments with NLM.

Original

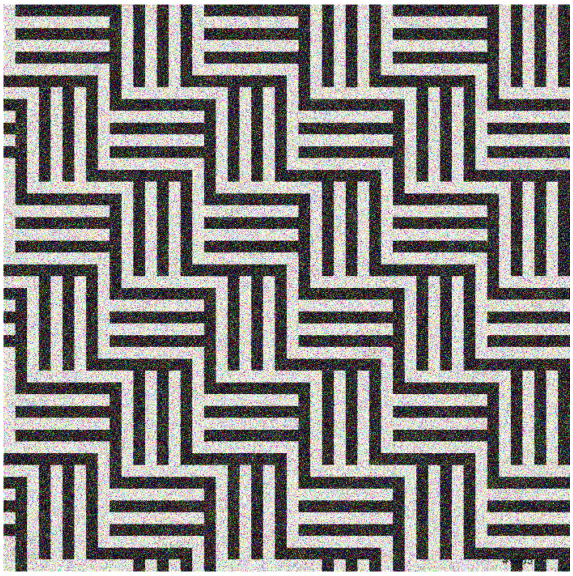
Noisy image (std=50)

NLM

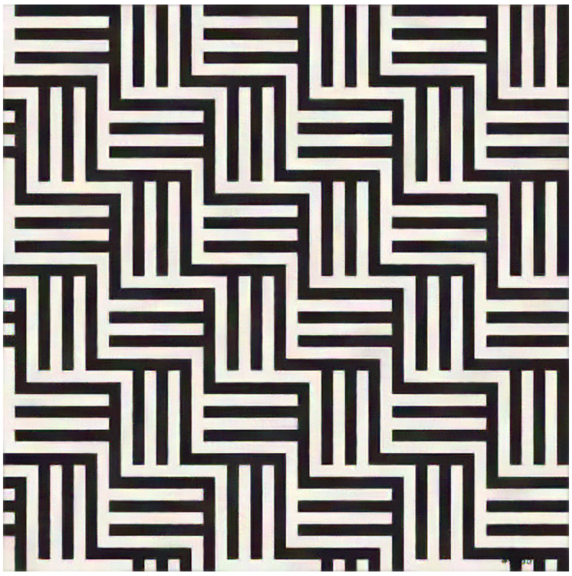
In this image NLM does a pretty good job at denoising. Despite being a method based on averaging, it managed to keep most of the details on the letters. After the denoising process all the text but the logo is readable. From all the other details, the logo seems to be the area with less “self-similarity”, in contrast of the letters which appear more times over the image.



Original pattern



Noisy pattern



NLM

Over this pattern, the results of NLM are great. The recovered image is indistinguishable from the original. In this context, where the pattern is repeated many times over the image, the denoising technique works great because it finds lots of similar patches for the aggregation. Finally, because it only does the average with similar patches, the pattern is preserved without blurring (as one would get by just averaging with close pixels without taking into account patch similarity).