Image Denoising - Homework 3 Report

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Exploring Patch Similarity in an Image

This paper describes an experimental procedure to analyze the self-similarity of an image. When we select a reference patch, the algorithm finds the most similar patches in the image (restricted to a window).

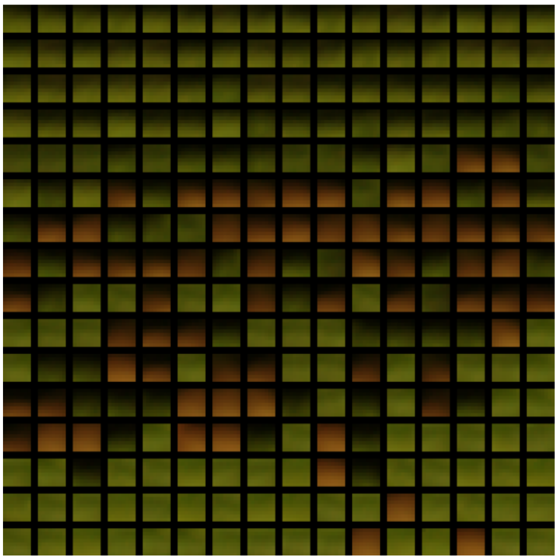
Firstly, we can check if the found patches are coherent by directly looking at them. We can also see the centers of the closests (i.e. most similar patches) to the reference, and closests to the last similar patch (the less similar in the list). If these centers are not too different in the two cases, then the results are coherent.

Secondly, two structure models for the structure of similar patches are computed. The first one is a Gaussian model (performed via PCA). Under this model, similar patches are sampled from a Gaussian centered at the average patch (denoised version of the reference patch). The PCA analysis also allows us to check if the representation is sparse (i.e. only a small number of coefficients is needed to construct a similar patch to the reference). The second model is a Gaussian Mixture with two clusters (done with EM). Here, the idea is to see if the cluster of similar patches can be divided into two.

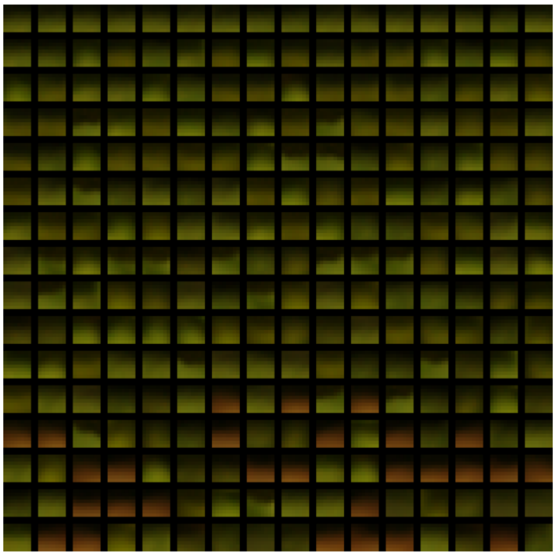
Edge patch

We start by analyzing patches similar to a reference centered in an edge, see Figure 1.

Figure 1: Center of reference patch selected (red dot)



(a) Window 100



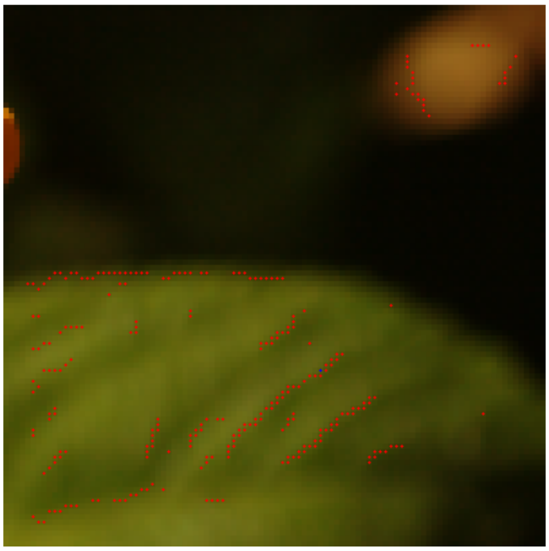
(b) Window 200

Figure 2: List of similar patches found for a patch of size 8x8 centered at Figure 1 red dot.

From Figure 2a we find that the last similar patches are not similar to the reference; they look more like a constant green value instead of an edge. We can use a bigger search window (200 instead of 100) and we should expect to find more actually similar patches. Indeed this is what happens, as seen in Figure 2b.

In addition, we see in Figure 3 that the centers of the closests patches to the reference and the centers of the closests patches to the last similar vary a lot for the window of size 100, suggesting that the last closest patches found are not actually very similar to the reference. The opposite is observed in the case of the window of size 200.

Centers of closests patches to the reference patch



Centers of closests patches to the last similar patch

Window size 100

Centers of closests patches to the reference patch

Centers of closests patches to the last similar patch

Window size 200

Figure 3: centers of closests patches to the reference (left column) and centers of closests patches to the last similar patch found (right column). The comparison is done using a window size of 100 (top row) and another of size 200 (bottom row).

Finally, we can also check the previous observation by looking at the histogram of the clostests patches to the list of similar patches found in Figure 4. This illustrates that, as 100 is not a big enough size of search, some of the similar patches found are actually part of the details of the leaf (not edges as the reference patch). Another important observation is regarding the sparsity of similar patches. It is clear from Figure 5 that only a small fraction of the PCA coefficients are non-negligible, thus the representation in the basis is sparse.
The Anderson-Darling normality test results are 0.0004, 0.0000, 0.0001. Therefore, it follows that the patches do not follow a gaussian distribution. Moreover, in Figure 6 we found that the Gaussian Mixture model found a reasonable partition of the patches. These correspond to the two leaves that present and edge with respect to the background.

(a) Window 100 (b) Window 200

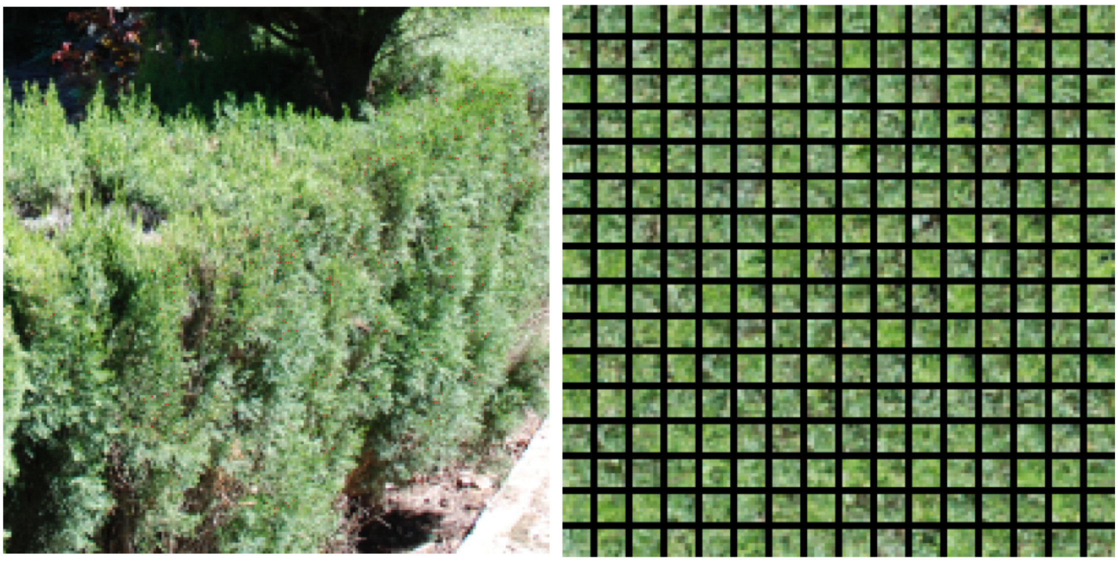
Figure 4: Histogram of the centers (in log-scale) of the closests patches to the list of most similar patches found.

Figure 5: Magnitude of PCA coefficients of the patch of Figure 1 with window size 200.

Figure 6: Centers of the patches that belong to the two clusters (red and blue) fund with the Gaussian Mixture model.

Texture patch

Now we proceed to study the case of a texture patch, Figure 7. The most different results lie in the sparsity of the representation on the PCA basis. The difference between the coefficients between Figure 5 and Figure 8 is noticeable; the PCA representation of a texture patch needs to yield much more non-negligible coefficients. This can be explained by the amount of detail that is needed to synthesize a texture patch since more specific basis patches of low variance are required. Lastly, in this case, the Anderson-Darling normality test results are 0.4272, 0.7159, 0.5774. Hence, the patches are correctly modeled with a gaussian distribution.



(a) (b)

Figure 7: (a) Texture region analyzed. (b) Similar patches found.

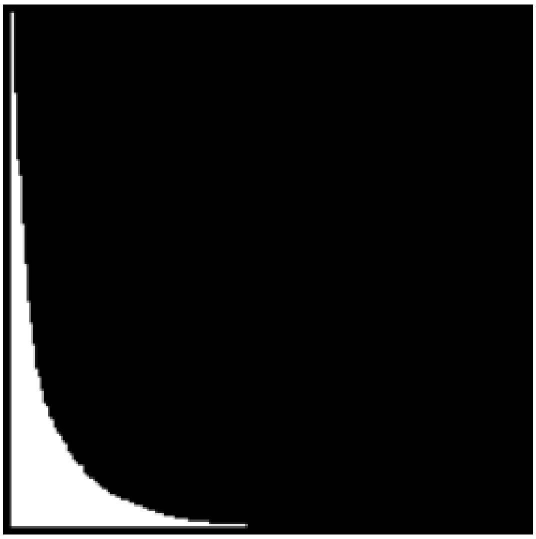


Figure 8: *Magnitude of PCA coefficients of the patch of Figure 7a with window size 200.*

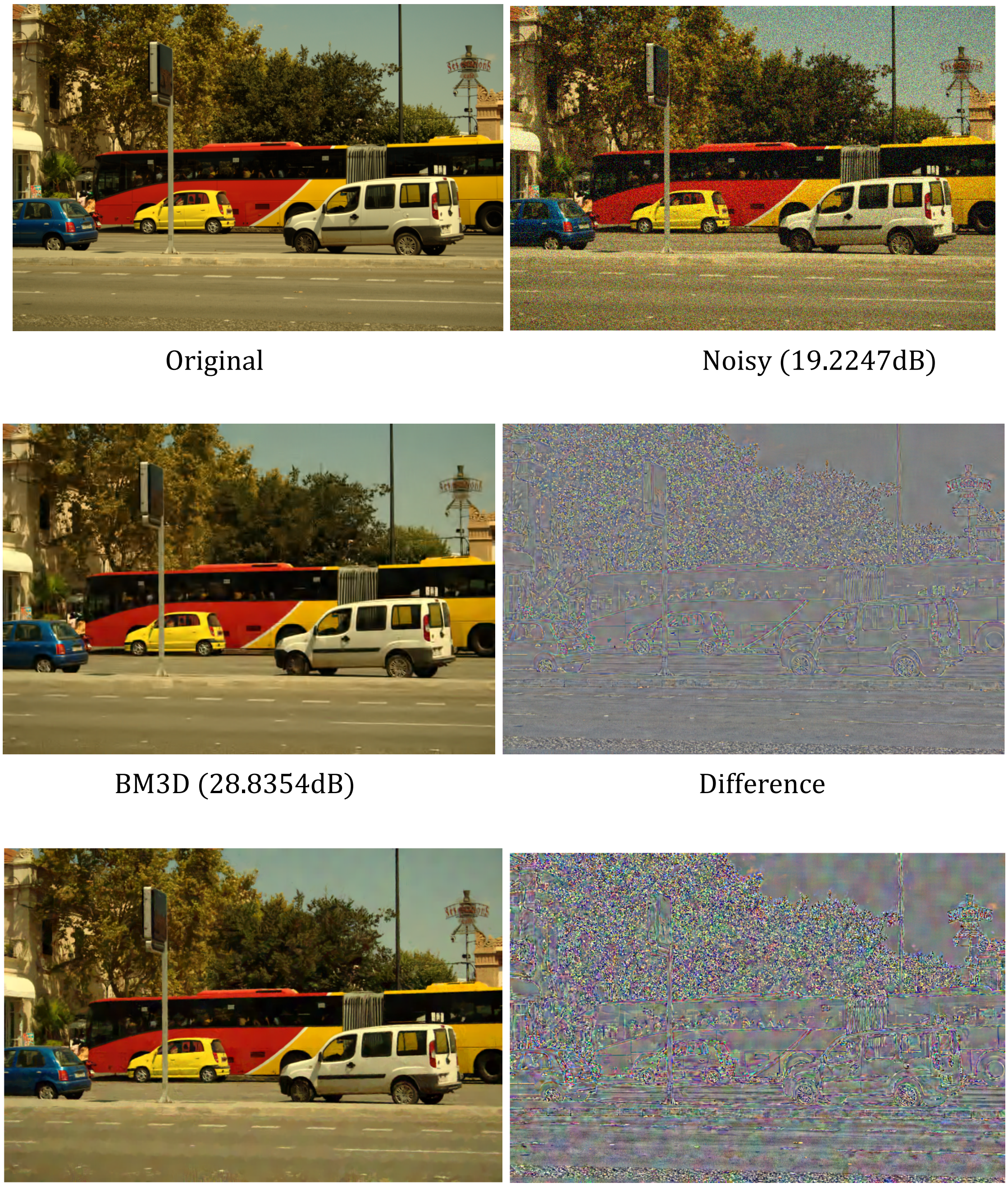
Conclusions

The most relevant conclusions from the experiments performed are:

- Suitable window size is needed in order to find good similar patches.
- Patches centered at edges have a sparse representation in the PCA domain; their effective dimension is low. The Gaussian model, in this case, is rejected. The mixture model makes sense since it captures patches centered at different leaves.
- Patches of textures have a high effective dimension, as illustrated by the big amount of non-negligible coefficients. In addition, they are correctly modeled by a gaussian distribution.

Non-Local Bayes

Like BM3D; NL Bayes is applied in two steps, with the results of the first one being used as an oracle for the second step.
Even though NLB achieves a slightly better PSNR, the visual results (in my opinion) are better for BM3D (which is especially noticeable in the difference image in Figure 9). In particular, NL Bayes introduces blurry artifacts in the street portion of the image as seen in Figure 10.



Original — Noisy (19.2247dB)

BM3D (28.8354dB) — Difference

NL-Bayes (29.0024dB) — Difference

Figure 9: General comparison for noise with σ=30 between Non-Local Bayes and BM3D.

Figure 10: Street detail comparison for noise with σ=30 between Non-Local Bayes and BM3D.

More comparisons are made in Figure 11 and Figure 12. In both cases the conclusions are the same: results of BM3D are better than those of NL Bayes. This behavior is especially noticeable in the difference images, where BM3D gets much better results in the edges of the objects.

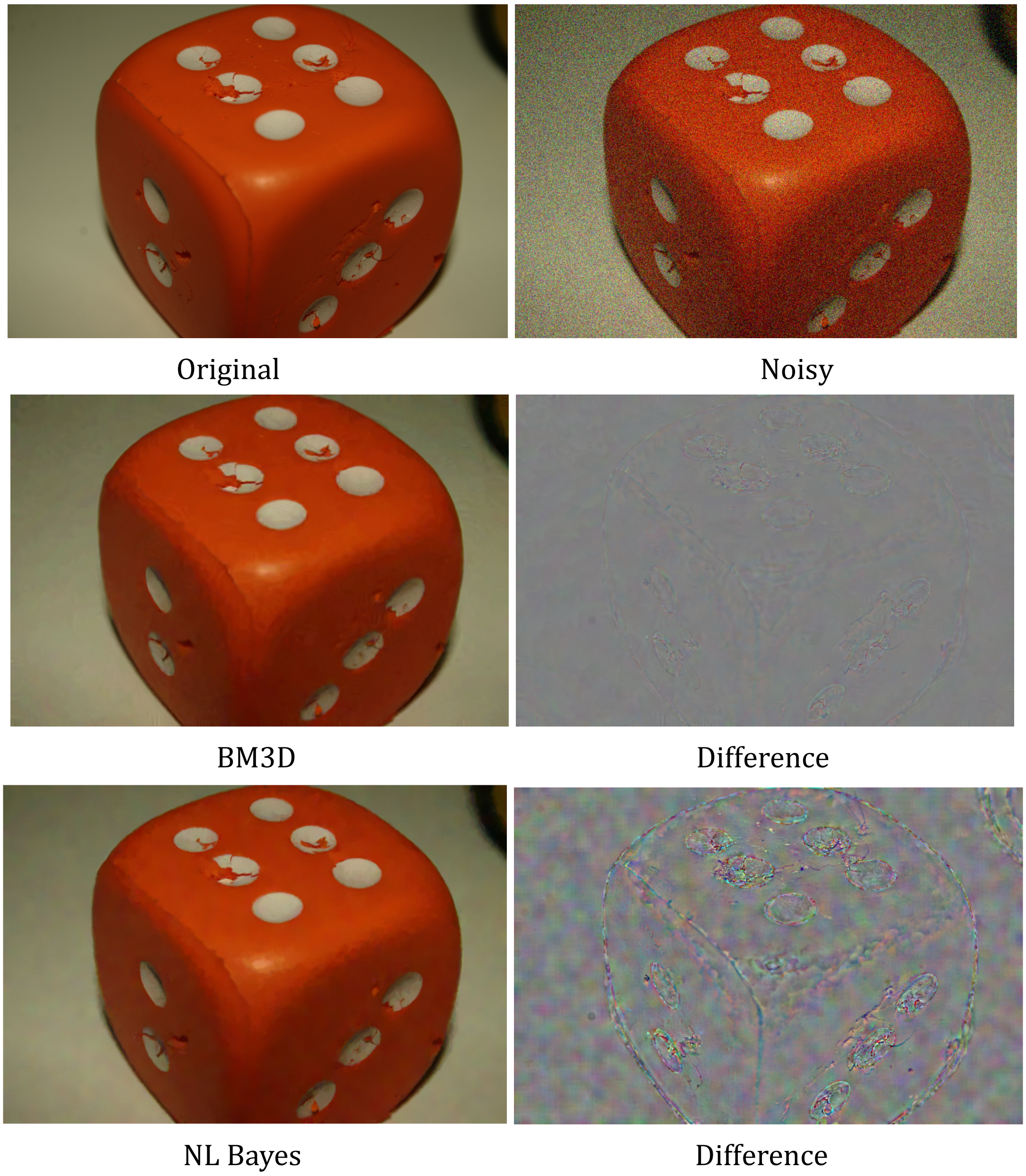


Figure 11: BM3D and NL Bayes results for noise with σ=30.

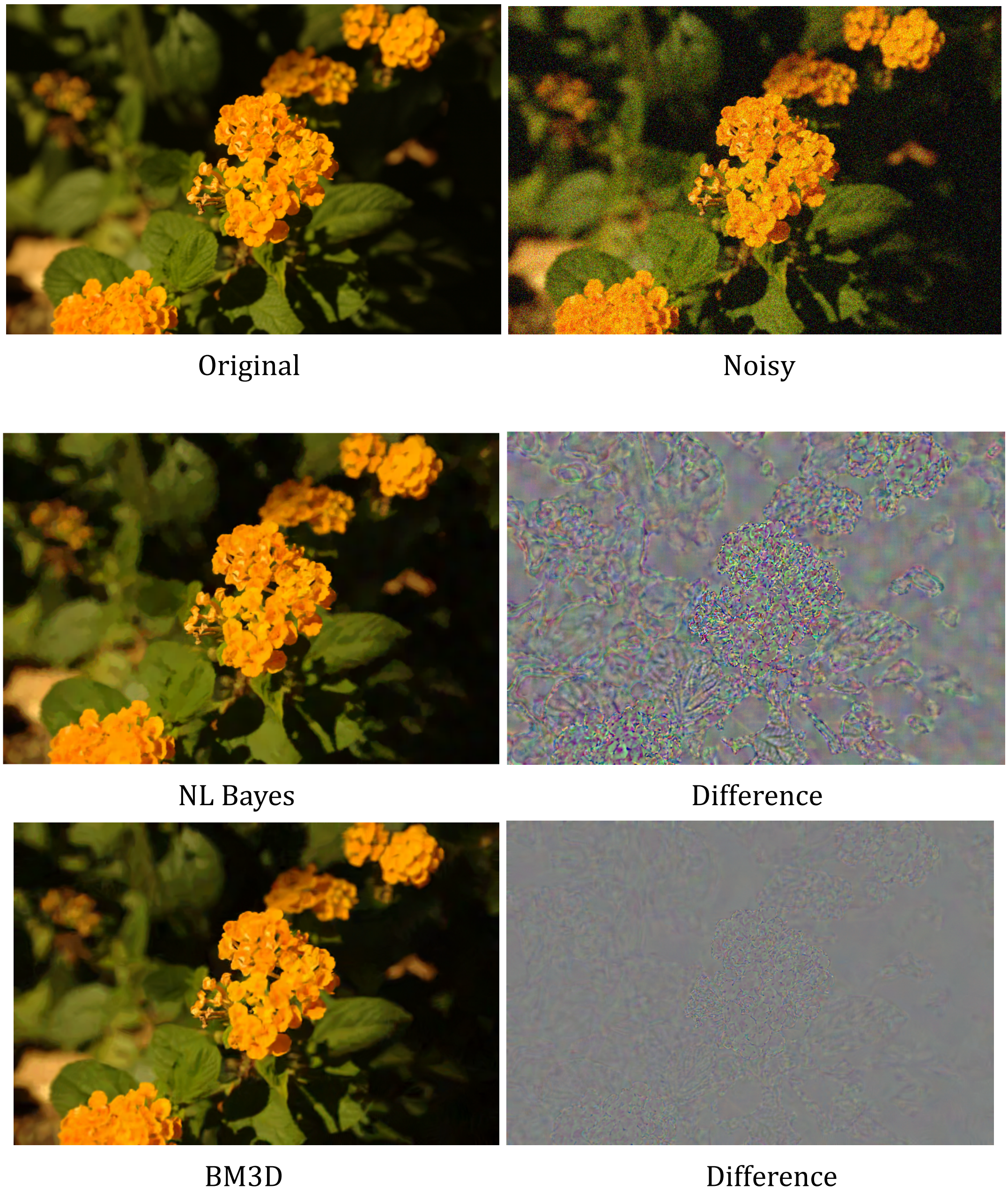


Figure 12: BM3D and NL Bayes results for noise with σ=30.

Conclusions

- Even though NL Bayes obtains good denoising results, the ones obtained with BM3D are better. The fact that BM3D is consistently better can be clearly seen in all cases on the difference image.
- The main problems of NL Bayes seem to be in the edges and non-homogeneous parts of the image.