Image Denoising - Homework 4 Report

MVA 2021-2022
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EPLL: An Image Denoising Method Using a Gaussian Mixture Model Learned on a Large Set of Patches

Maximum rank considered for the covariance matrices (in percentage): 100 so slow that it times out.

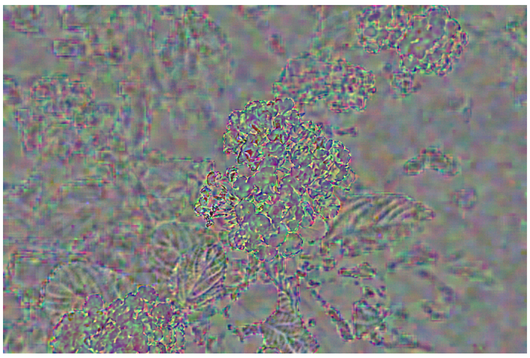
Effect of scales

Firstly, we try the algorithm with all the possible scales (1, 2, or 3) and compare the results with the ones obtained with BM3D. As seen in Figure 1, the results of BM3D are notoriously better, especially the fine details of the flower. Moreover, using more scales does not improve the results; they get worse. Similar results are observed in Figure 2 regarding the effect of the scales. However in this case the denoising is better since the image hasn't got as many details as in Figure 1; the dice and the background are homogeneous regions.

Original

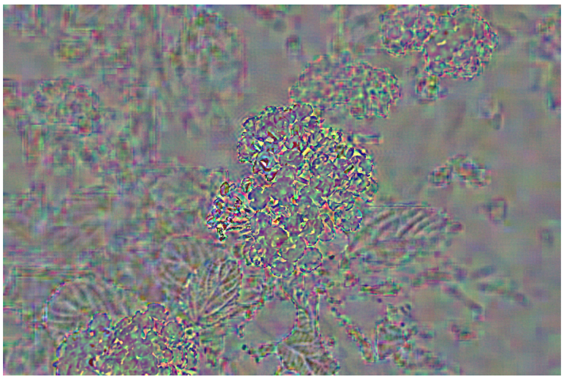
Noisy

Single scale



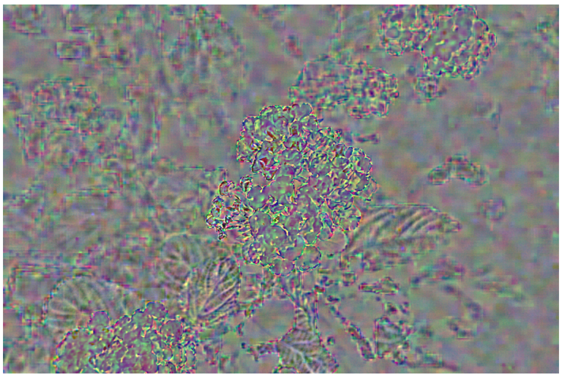
Difference

Two scales



Difference

Three scales

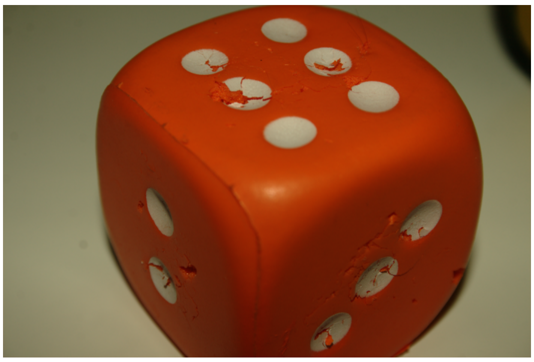


Difference

BM3D

Difference

Figure 1: Comparison between EPLL (maximum rank 50) for the three possible scales and BM3D for noise with σ=30.



Original

Noisy

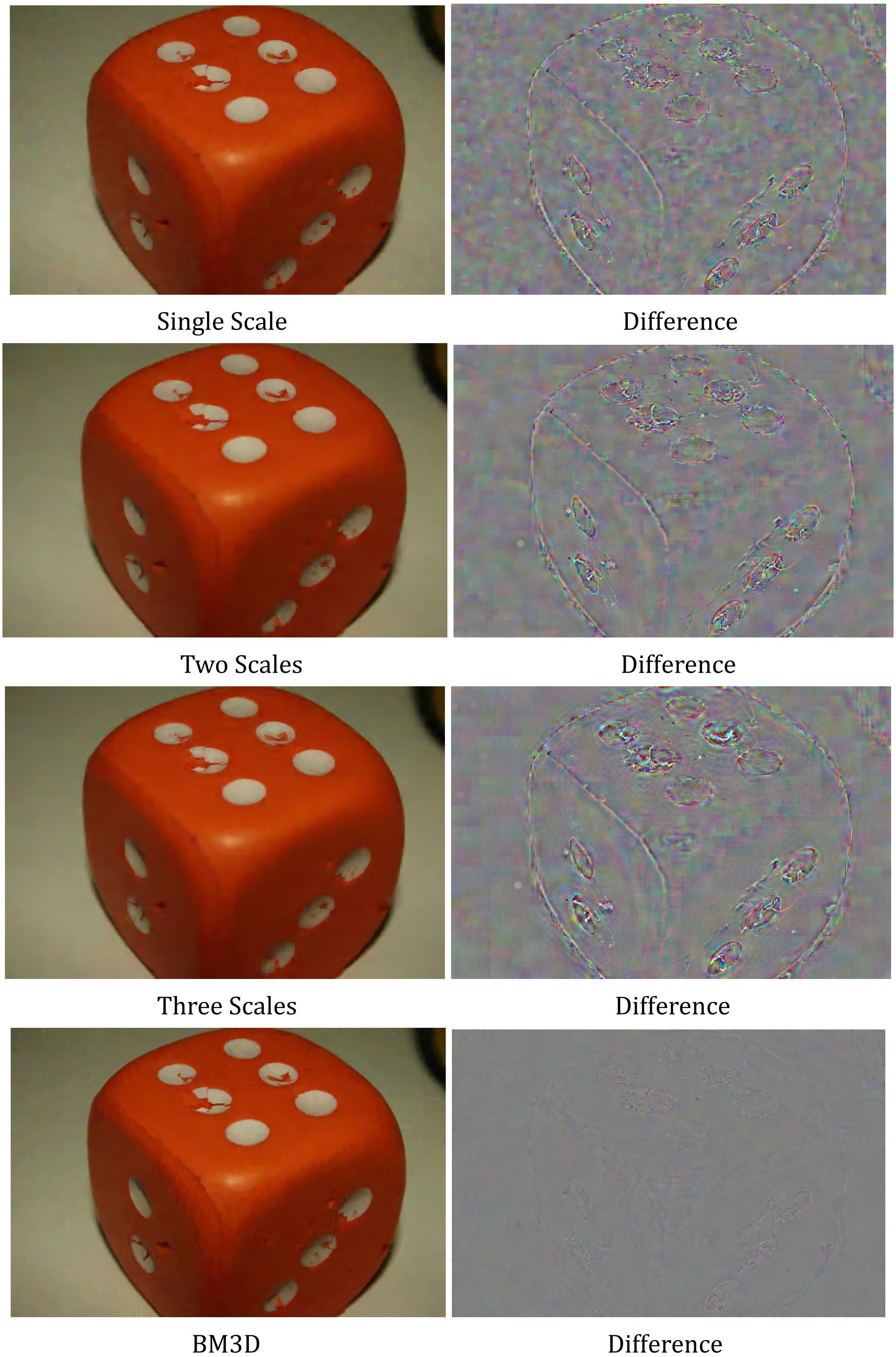
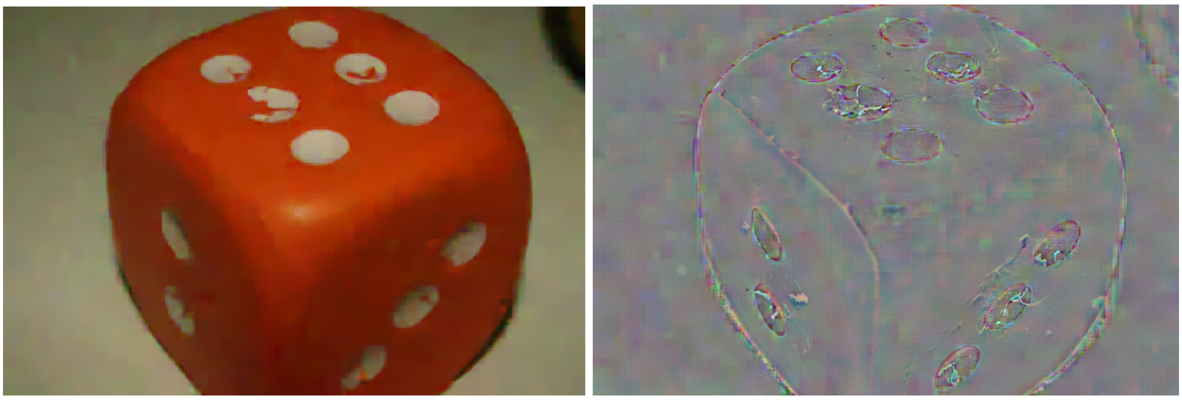


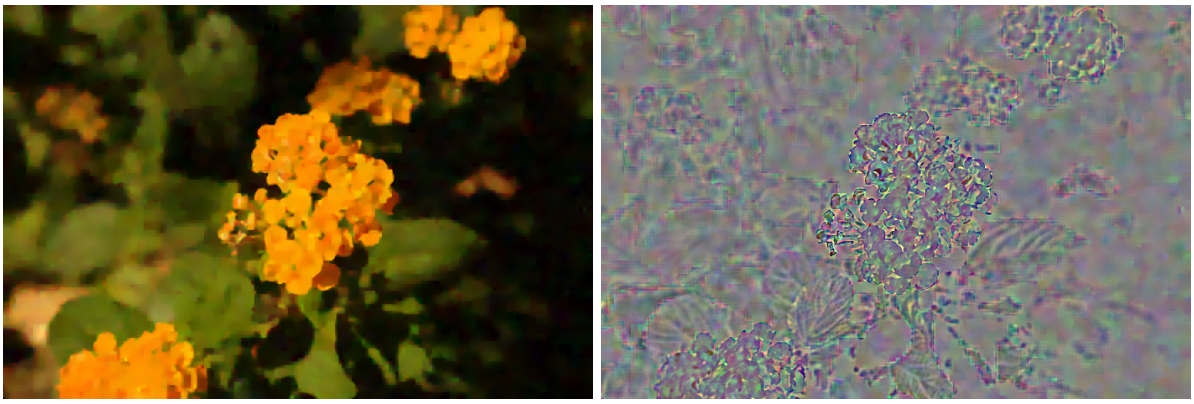
Figure 2: Comparison between EPLL (maximum rank 50) for the three possible scales and BM3D for noise with σ=30.

Effect of increasing noise

Based on the results of the previous sections we only report the results with a single scale. Now we corrupt the image with more noise and observe if the performance is significantly degraded. From Figure 3 we see that the effect of more noise is more noticeable in the image of the flower; more detail is lost on the leaves and petals. In contrast, for the dice, the result is almost the same but more smooth.



Single Scale Difference



Single Scale Difference

Figure 3: EPLL denoising (maximum rank 50) for noise with σ=60.

Conclusions

- The algorithm is very slow; for example, a 100% maximum rank times out the demo.
- The multi-scale approach seems to degrade the results. Several artifacts are observed when the number of scales increases.
- EPLL over-smooth texture areas and small edges.
- The visual quality of the results is not bad but BM3D is consistently better in all the images tested.

Zoran Weiss GMM

The authors learned a GMM model for the prior distribution of patches. The results obtained show some interesting results that show us the structure of the model.

Figure 4 shows the first component of the model. The probability is quite high (0.00363) and has a sparse representation. This corresponds to flat patches (they don't require many coefficients) as seen in the samples.

The second component we show is the fourth, in Figure 5. Note that the probability has dramatically decreased to 0.00072. This component is interesting because it models patches with oriented edges.

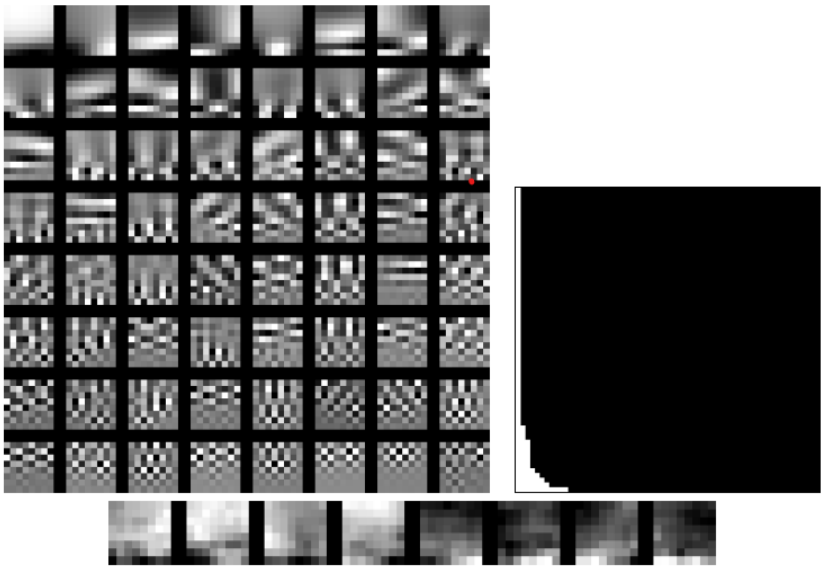


Figure 4: Eigenvalues and Eigenvectors of component 1 of the GMM. Probability 0.00363.

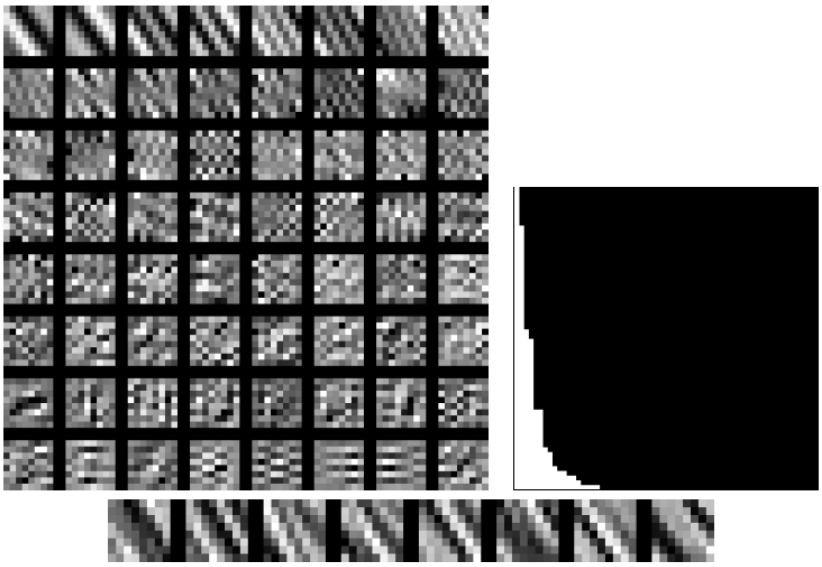


Figure 5: Eigenvalues and Eigenvectors of component 4 of the GMM. Probability 0.00072.

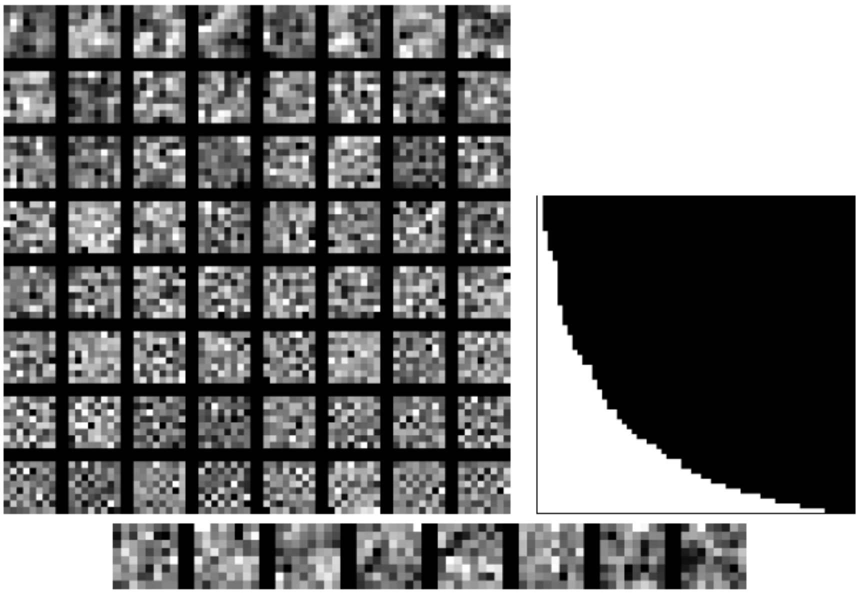


Figure 6: Eigenvalues and Eigenvectors of component 12 of the GMM. Probability 0.00010.

Finally, the samples and the non-sparse representation of the component of Figure 6 shows that it corresponds to patches of natural textures. These three examples show the expressiveness of the learned GMM.