Image denoising: cours 1

Experimental report

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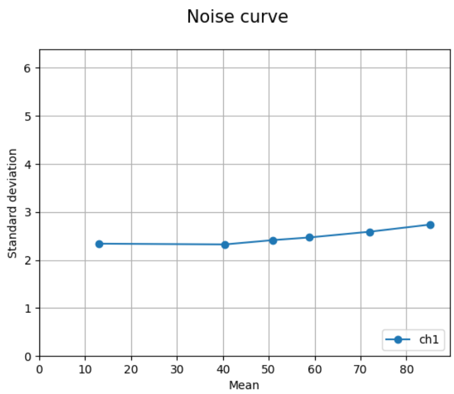
Analysis and Extension of the Ponomarenko et al. Method, Estimating a Noise Curve from a Single Image

Summary of the article

In this article, the authors propose a simple method for estimating the noise in an image. The method is first introduced for estimating the variance of AWGN, but then is extended for estimating the variance of noise that depends on the intensity of the image.
The method is based on performing the DCT of overlapping patches of the images. It splits the coefficients of the DCT into two disjoint sets: high frequency coefficients (which also include the mean component (i+j=0)) and low frequency coefficients. Then, it selects the patches whose variance of the low frequency coefficients is lower, the intuition here is that those patches correspond to the most regular patches (without edges and textures, so the variance in high frequency will be mostly because of the noise), and estimates the noise as the median of the variance of the high frequency coefficients for those patches. The extension for signal-dependent noise is done by creating bins of patches based on their mean intensity, and then applying the method per bin, ending up with a noise curve with one noise value per bin.

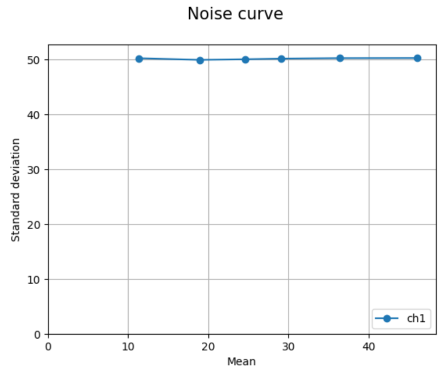
Experiments

First, I verified its results over images with artificial noise, where it produced pretty accurate results even in the context of low noise over an irregular image. When the noise is high the estimate is almost perfect.



“bag” with artificial noise of variance 4

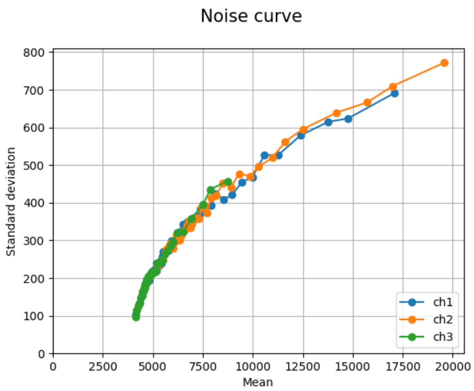
Result for “bag” with artificial noise of variance 4 (it’s close to the real value of 2)



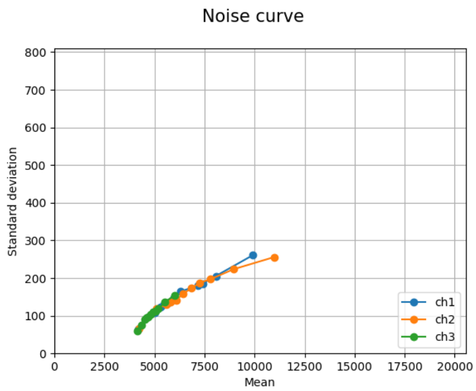
“stairs” with artificial noise of variance 2500
Result for “stairs” with artificial noise of variance 2500 (almost perfect)

Then, I tried the algorithm on raw images (with natural noise) and since in this situation there’s no ground truth, I can only verify that when the image is downscaled by a factor of 2, the standard deviation of the noise is reduced by 2. This effect is clearly visible on the following curves.

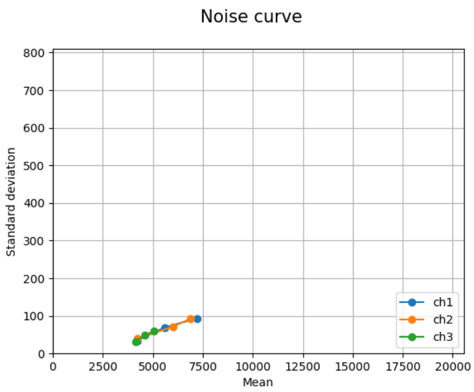
Raw image for the experiment

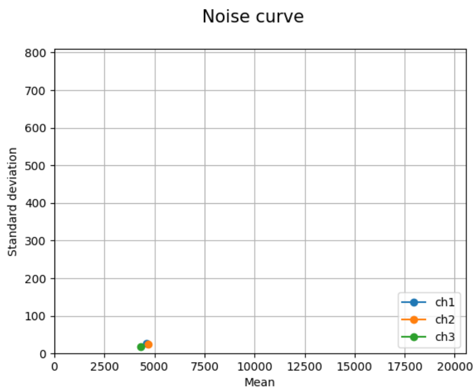


Scale S0



Scale S1





Scale S2 Scale S3

Finally, I observed that when increasing the down-scaling, due to computing the mean of bigger blocks of pixels, the image ends up having less different mean intensity bins (it’s more uniform), so the curve is only estimated in very few values.

Multi-Scale DCT Denoising

Experiments

Initial experiment with noise std = 40, DCT size = 8, scales = 5, frec = 0.4


Original image

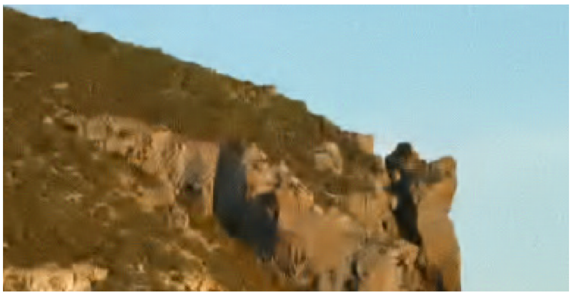

Noisy image (16.7274dB)


Single scale DCT(28.706dB)


Multi scale DCT(28.9495dB)

The benefits of using a multi-scale approach are noticeable if one observes the most regular parts of the image (the sky and the ocean). As the authors say, the problem with a single-scale approach is the residual noise in low frequencies, by adding the multi-scale step, the algorithm is able to get a more refined processing of the low frequencies and eliminates more noise. In the rest of the image, the differences between DCT and MS-DCT aren't so evident. Overall, both algorithms improve the quality of the image, which can be seen visually and on the PSNR.

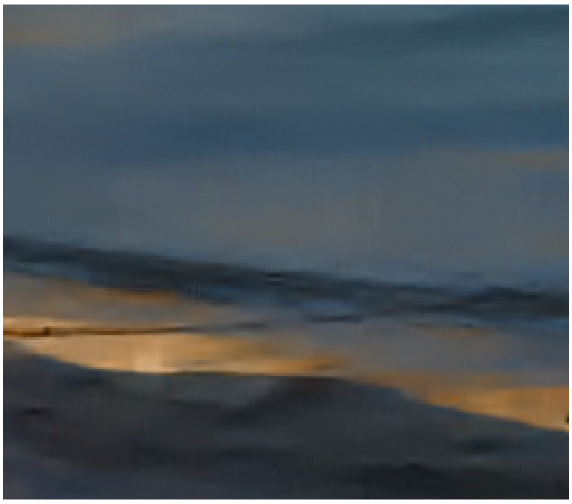
Now let's analyse the effects of the adaptive weights for the reconstruction of the pixels based on multiple overlapping patches. For that, let's take a closer look at regions with edges, such as the cliff.

MS DCT without adaptive aggregation MS DCT with adaptive aggregation

The use of adaptive weights is crucial for obtaining good results around edges. When adaptive weights are not used, artifacts such as the halo effect appear around the edges. Those adaptive weights are calculated for minimizing the variance of the estimator of the pixel, which is formed by the overlapping patches, favoring patches with the most sparse representations.

As a final comment for this experiment, although the results are great despite the initial noise, there are some details which are really hard to distinguish from noise, so are impossible to recover. For example, the pattern in the sea and the texture of the sand.

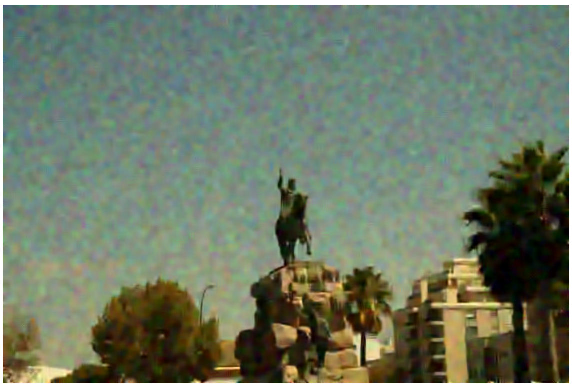



Original image MS DCT

Experiment varying the noise standard deviation (75, 100)

In a context of higher noise, the difference between single scale DCT and MS DCT gets more evident. For these higher noise values, the results with single scale DCT are pretty bad, especially over the sky region. Finally, the results of the MS DCT are surprisingly good even with noise of std 100. It's reasonable to observe that the higher the noise, the more mid and high frequency details are lost, nevertheless the results are still great.

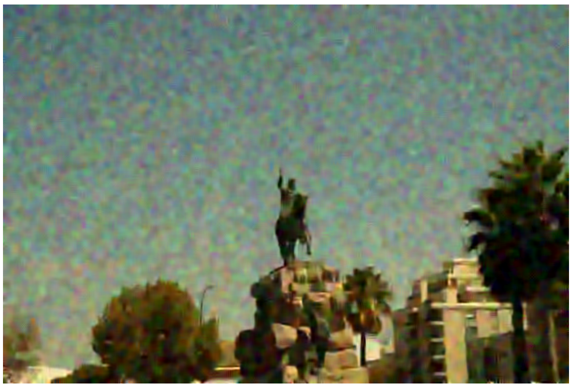
Noisy image (std = 75)



Single scale DCT (std = 75)

Multi scale DCT (std = 75)

Noisy image (std = 100)



Single scale DCT (std = 100)

Multi scale DCT (std = 100)