

# Image Denoising

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## Article 1: Ponomarenko's method:

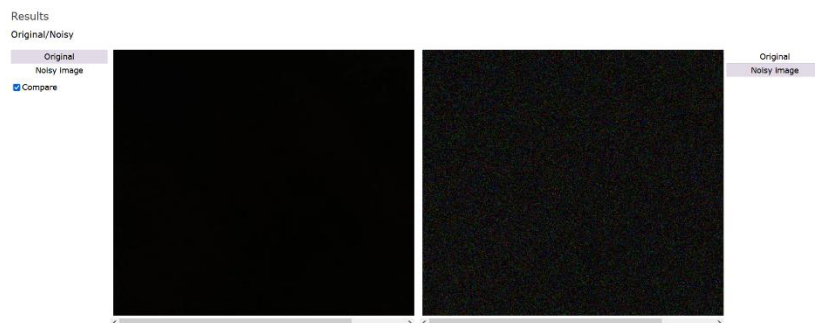
### Summary:

The aim of this method is to estimate the variance of the noise in the image. To do so, they use the idea that in a uniform patch, the information is concentrated in the medium frequency and thus the high frequencies only represent noise. Hence, they can be used to estimate the variance of the noise. In practice, in each patch, the norm 2 on the coefficients of the low frequencies is computed. If this measure is low, as the information of most images (not textured) is encapsulated in the low and medium frequency, it means that the information is mainly in the medium coefficient. Thus, the patch is quite uniform. Thanks to this method, the patches are ranked from the most uniform to the least. For each high frequency, an estimation of the variance of the noise is computed on the coefficients of the K most uniform patches. The best K has been proved to be the position of the 0.5-quantile in the ranked list of patches. As the noise is uncorrelated and uniformly distributed among all the high (and low) frequencies, the final estimator of the variance of the noise is the median of the estimators on the high frequencies.

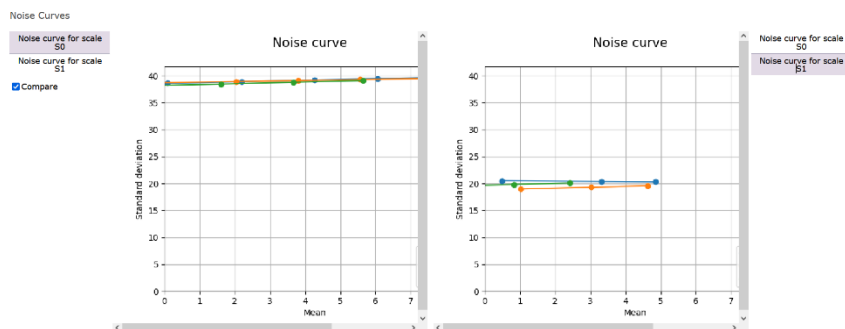
### Experimental report:

We applied on each example a white noise of variance  $\sigma^2 = 1600$ .

### Uniform image:



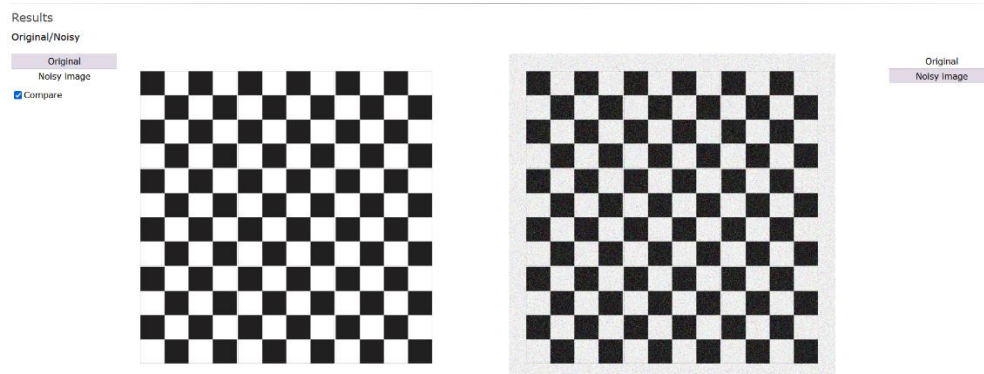
Uniform black image with and without the additive white noise



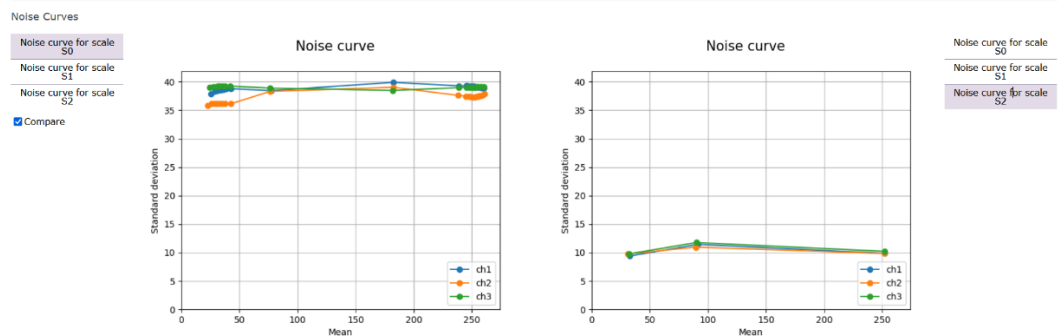
Curves of the Ponomarenko estimated noise for a black uniform image (scale S0 and scale S1)

The error between the estimator and the real noise (40 for S0, 20 for S1) is weak for every scale. In fact, at every scale, there exist uniform patches on which high frequencies only represent noise.

### Chessboard image:



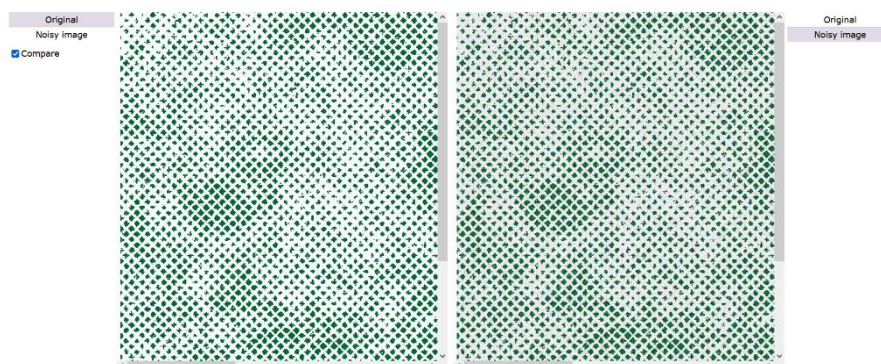
Chessboard image with and without white additive noise



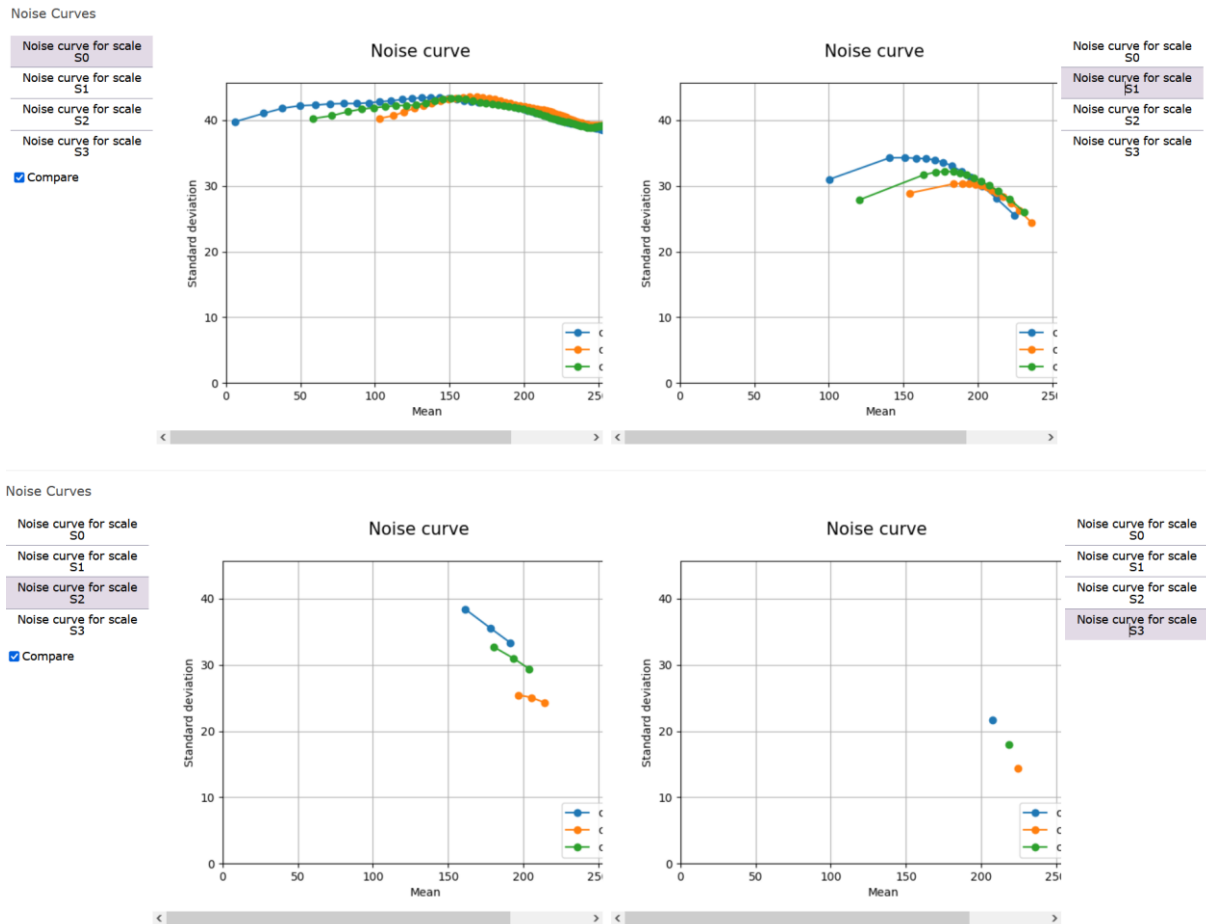
Curves of the Ponomarenko estimated noise for a chessboard image (scale S0 and scale S3)

On a large scale (S0) some information is encapsulated in high frequencies because the pattern of the image is more complex. In other terms, the algorithm does not find perfect uniform patches on which to compute the noise. Hence, the error of the Ponomarenko estimator is higher than in uniform image. However, on smaller scale (S3) the pattern is less complex (and still redundant), thus there exist better uniform patches. As a consequence, the estimator fits the real noise standard deviation (=10) on small scale (S3).

### Textured image:



Textured image with and without additive white noise



### Curves of the Ponomarenko estimated noise for a textured image (scales S0, S1, S2, S3)

In textured images, the information is not only encapsulated by low and medium frequency but also by high frequencies. The assumption of the Ponomarenko method that  $V^H$  is an estimator of the noise is wrong (at any scale). Hence its poor results at any scale. In other words, no matter the scale, there exists no uniform patches on which compute the noise.

**Remark:** we can note that the standard deviation of the real noise is divided by 2 between two scaling operations  $S_k$  and  $S_{k+1}$ . More than the scale, the transformation must affect the values, intensities of the image.

### Article 2: Multi-scale denoising

#### **Experimental report:**

In the dice image, the big difference between one-scale DCT denoising results and multi-scale denoising result is observed on uniform zones (red surface of the dice, white support). Compared with the noisy image, the one-scale denoised image presents low frequency noise. The goal of MS denoising was to remove this noise and it works. Yet, in the white spots of the dice, noise remains for both denoising methods and some textured (scratched white spot on the top of the dice) are blurred by both methods. In fact, the texture's information is supported by high frequency coefficients for any scale. Thus, this information is mixed up with noise and removed during the denoising.

In the second image, this phenomenon is even more noticeable. The texture of the skin is totally blurred by MS denoising. In fact, in the one-scale denoised output, one can still notice a bit of skin texture inside the remaining low frequency noise, hence its removal by the MS denoising algorithm.

We can also note that because of this texture, visually the MS denoising algorithm performs poorly on the zoomed face image compared with its result on the dice image. This is also confirmed by the fact that the MS denoised dice image has a greater PNSR than the MS denoised zoomed face image whereas the initial PNSR of their noisy (hence of the input) is similar.

### Dice image:

Denoising results

- DCT 1 scale
  - MS DCT noagg
  - MS DCT hard
  - Original
  - MS DCT**
  - Noisy
  - diff DCT 1 scale
  - diff MS DCT
- ☒ Compare



- DCT 1 scale
- MS DCT noagg
- MS DCT hard
- Original
- MS DCT**
- Noisy
- diff DCT 1 scale
- diff MS DCT

### Original and noisy (16.79dB) images (additive white noise of standard deviation of 8)

Denoising results

- DCT 1 scale
  - MS DCT noagg
  - MS DCT hard
  - Original
  - MS DCT**
  - Noisy
  - diff DCT 1 scale
  - diff MS DCT
- ☒ Compare

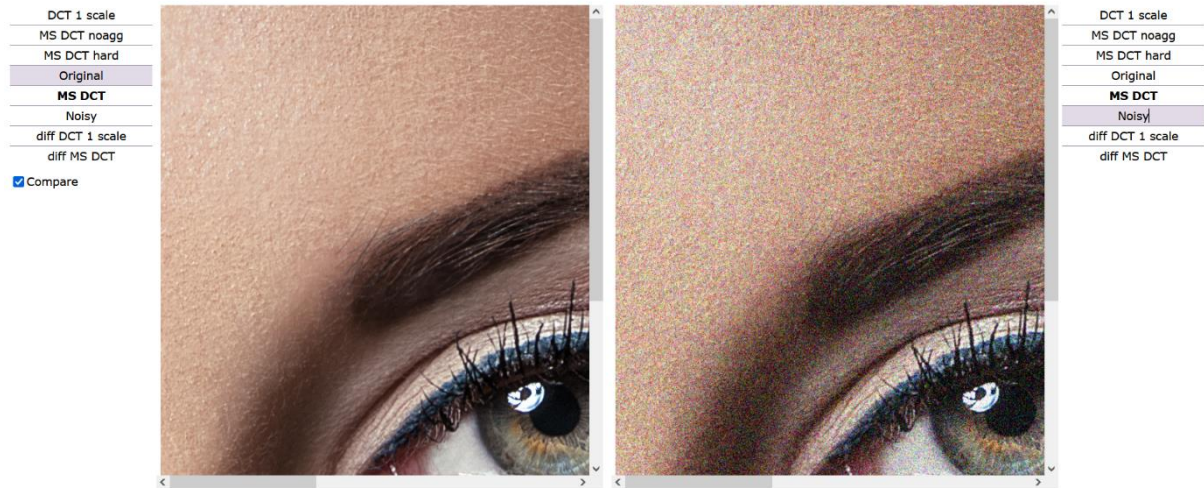


- DCT 1 scale
- MS DCT noagg
- MS DCT hard
- Original
- MS DCT**
- Noisy
- diff DCT 1 scale
- diff MS DCT

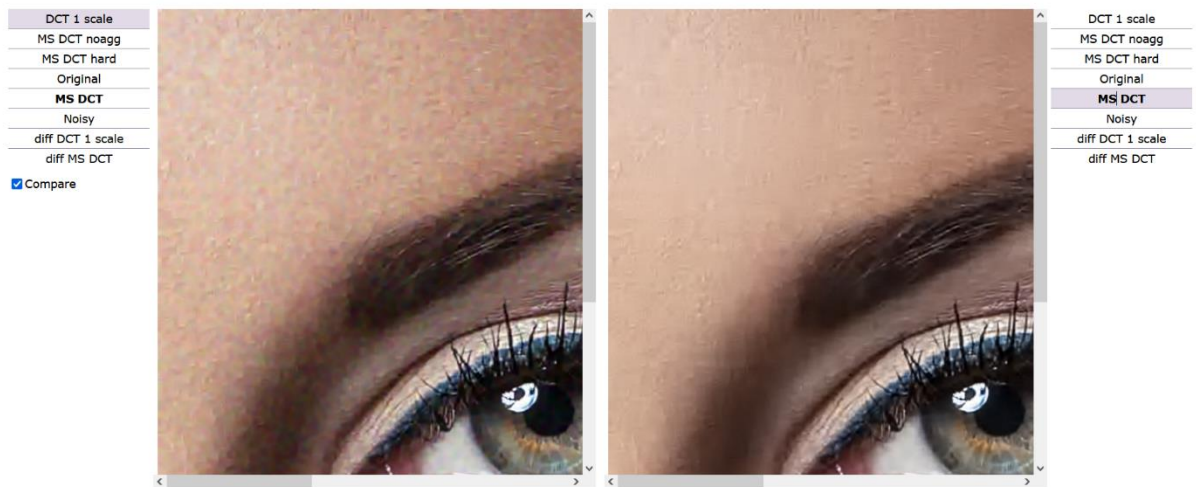
### One-scale denoising method's (34.58dB) output and MS denoising method's output (36.67dB)



Zoomed face image:



Original and noisy (16.97dB) images (additive white noise of standard deviation of 8)



One-scale denoising method's (29.89dB) output and MS denoising method's output (30.4719dB)