Image denoising
Experimental assignment Course 1

Denys Sikorskyi

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

1.1. Thoughts on the Ponomarenko et al. Method

In the paper "An Automatic Approach to Lossy Compression of AVIRIS Images" N.N. Ponomarenko et al. propose a new method to compress AVIRIS images. However, during this approach new noise estimation algorithm is presented. It is based on the computation of the variance of overlapping 8x8 blocks. The noise is estimated on the high-frequency orthonormal DCT-II coefficients of the blocks. The obtained labeling frequency coefficients are labeled as low and high frequencies. Low frequencies will be used to calculate the empirical variance of each block and high frequencies are connected with edges, structural or textual information. As the algorithm utilizes only low frequencies it is unimpacted by edges and other high-frequency information. Obviously, the blocks with the lowest energy values are likely to contain only noise generally designated by high frequencies, so next the algorithm calculates the empirical variance of the high-frequency coefficients of the selected blocks with the lowest measured energy. There are two approaches for choosing the number of selected blocks. The variant of setting a small percentile of 0.5% of total variances tends to be more effective than the adaptive strategy of selection. In the end, the algorithm computes the median of the last obtained variances and returns the result of noise estimation.

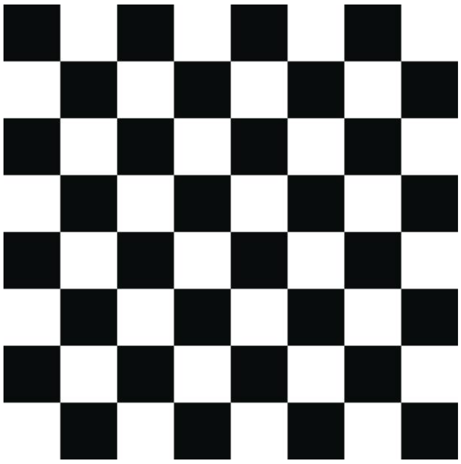
2. Some experiments on the algorithm

Let’s test the algorithm on a set of images. Per-patch method is used where the noise is estimated within every single patch. The algorithm differentiates low and high frequencies which will help avoid the influence of high-frequency image structures on noise estimation. We will try a chessboard image, a texture, and a flat image.

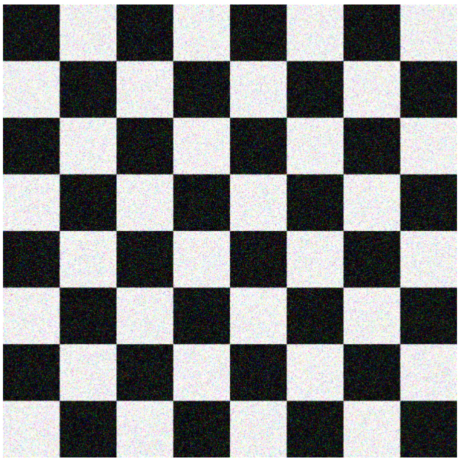
2.1. Chessboard image

We will use a simple chessboard image and the noised version of it.

Images:

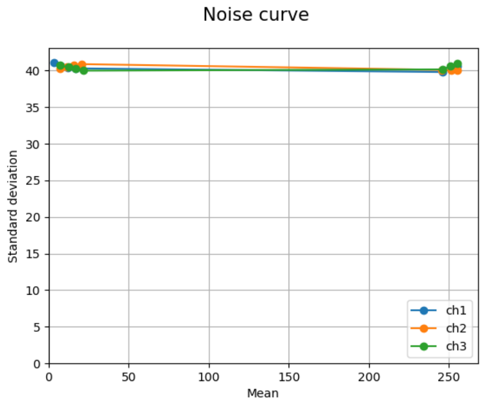


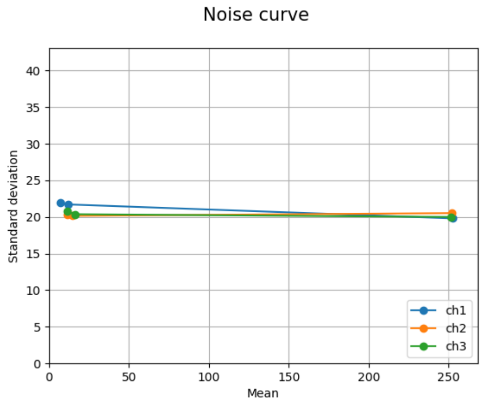
Chessboard image without noise

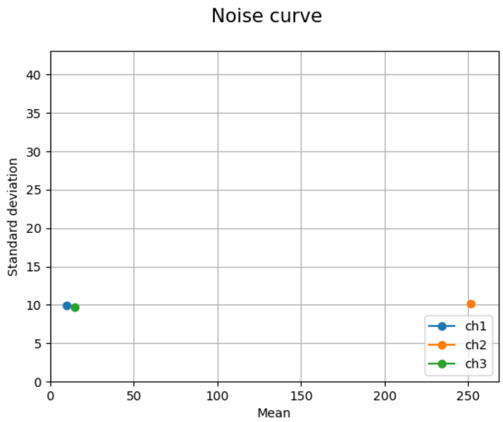


Noisy chessboard image

Graphs:







The graphs present the estimation of noise in the scales of the images, where we zoom by a factor of 2 in the next case. Zooming in the image implies having fewer points in the curve and in the gray-level axis because we have fewer pixels so fewer patches. We also observe that the standard deviation of the noise is almost divided by 2. It is obvious that the presented image is periodic, so lots of discontinuities exist. Therefore, we have high frequencies while applying DCT, so we can expect biased noise estimation. However, from the figures, we can see that the estimation of standard deviation is close to the applied one. This show that the algorithm is effective on images with discontinuities. The concentration in two different values of standard deviation can be misleading but this is due to the shape and intensities of the input image. Plus, both values are still in the range of the truly applied noise.

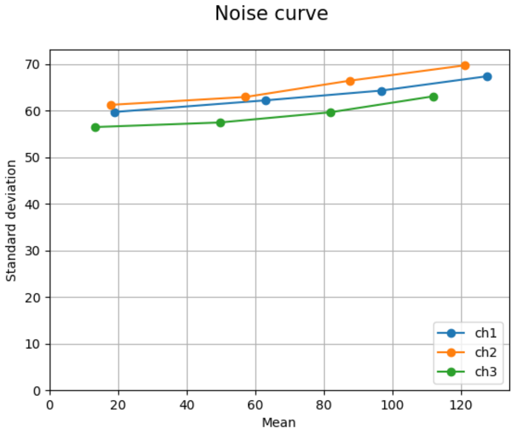
2.2. High textured image

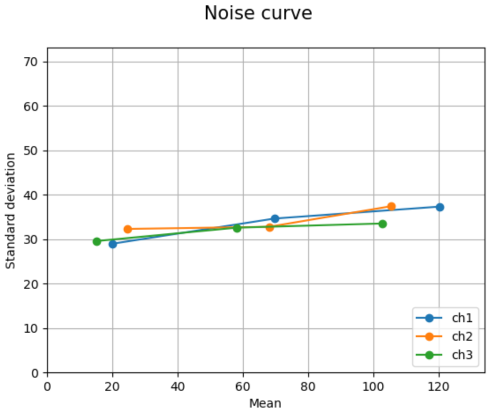
Images:

Firewoods without noise

Noised firewoods

Graphs:

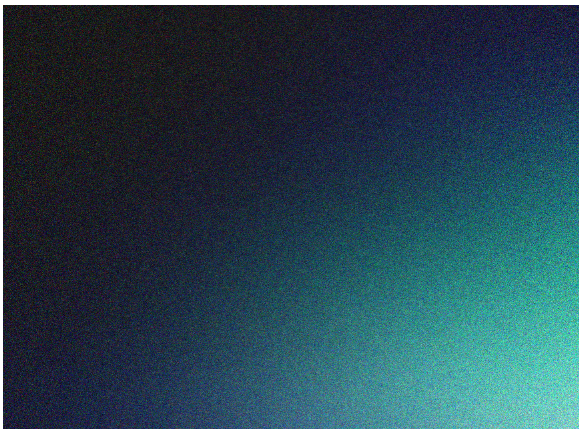




The main difference from the previous image is that in a particular range of pixel intensities the pixels' estimated standard deviation isn't concentrated, but it is concentrated around a particular value that is very close to the applied noise value. In this high-texture image, we can see the repeated structure, so we have high frequencies in the DCT domain. These frequencies are the result of the texture of the image, not of the applied noise. However, it is not a problem for the algorithm and the value of the noise standard deviation is estimated correctly. We can conclude that the algorithm also works for high-texture images.

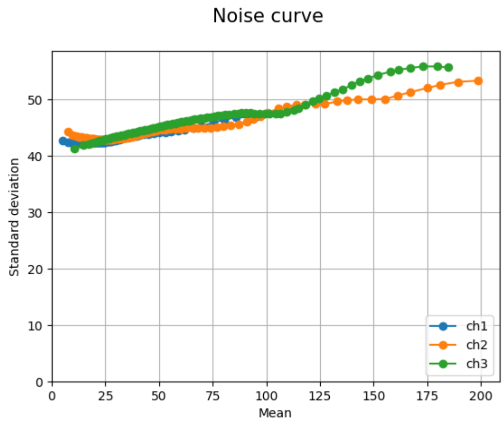
2.3. Flat image

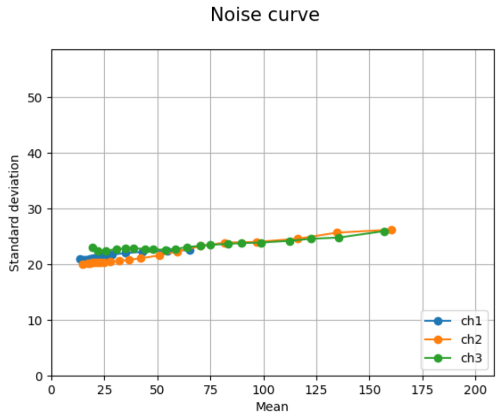
Images:



Base flat image *Noised flat image*

Graphs:





Each channel's estimation value of the noise is in the same range as the applied value, so the algorithm works effectively for flat images.

3. Experimental report for "Multi-Scale DCT Denoising"

In the paper, two algorithms evolved from DCT are presented. In the first, a two-step approach is utilized in the algorithm. At first, it applies at first local DCT to denoise the image patches and secondly estimates the empirical Wiener filtering factors. In the second, a multi-scale approach is used. The decomposition of the image in a dyadic DCT pyramid is performed. Then the single scale denoising to all scales is applied and finally fusion of the obtained estimates. The paper shows the superiority of the two algorithms compared to classic DCT. The multi-scale DCT has shown the best performance.

3.1. Experiments

Images:

Original image *Noisy image with sigma = 40*

1step DCT *MS DCT*

In the 1step DCT image, the sky became blurry. In other words, it is a flat image are with low-frequency coefficients which are not taken into account because this algorithm performs at a single scale. Contrary, in the MS DCT the sky looks like in the original image. Also, ringing artifacts, especially around the roof is present in the first denoised image, but they are much less visible in the second one. To sum up, MS DCT outperforms 1step DCT in flat areas and on textures and contours.

3.2. Parameters

3.2.1. Patch size

Let’s analyze the results of the change of some parameters.

Images:


1step DCT (4x4) 26.556dB *MS DCT (4x4) 27.1702dB*

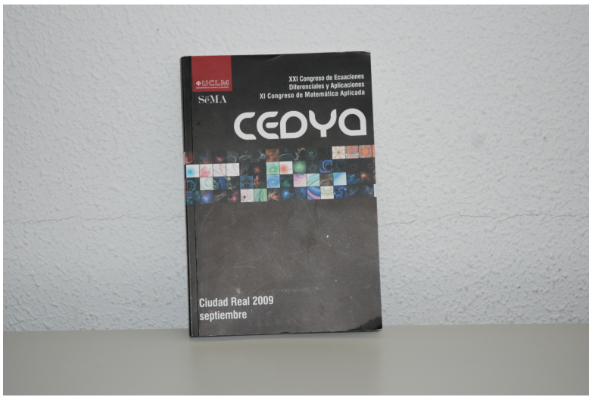

1step DCT (8x8) 27.389dB *MS DCT (8x8) 27.5573dB*


1step DCT (16x16) 27.375dB *MS DCT (16x16) 27.3538dB*

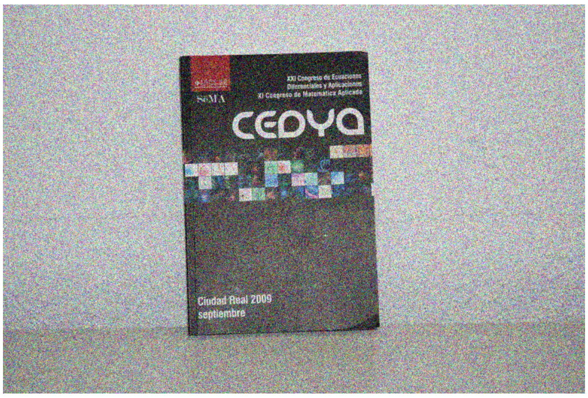
With the increase of the patch size used for denoising, the PSNR increases for both algorithms but stops at some size. The PSNR difference between MS DCT and 1step DCT is smaller as the patch size is greater. This small difference is presented in the images, the sky looks much more similar with fewer artifacts when the patch size is increased. For the larger patch, DCT operates at a larger scale, so we have less noise variance.

3.2.2. Aggregation

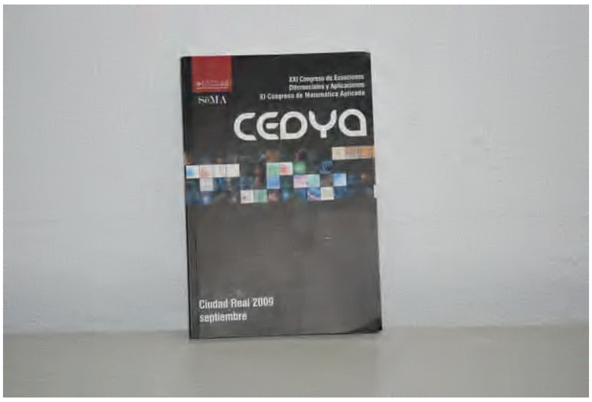
Images:



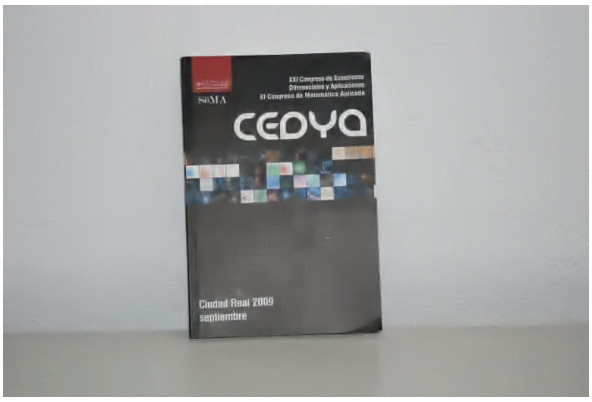
Original image



Noisy image with sigma = 40



MS DCT no aggregation



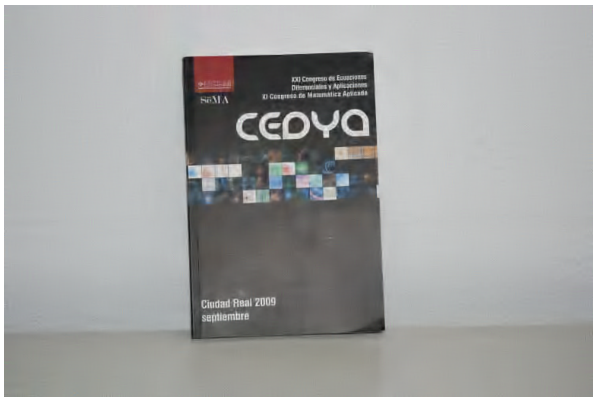
MS DCT with aggregation

On the MS DCT image with no aggregation exists some ringing artifacts, especially between the letters and edges. However, on the image with aggregation, the artifacts are almost visible. This can be explained as the result of the patch-wise DCT denoising step of the MS DCT. As the result, aggregation prevents the formation of highly visible ringing artifacts.

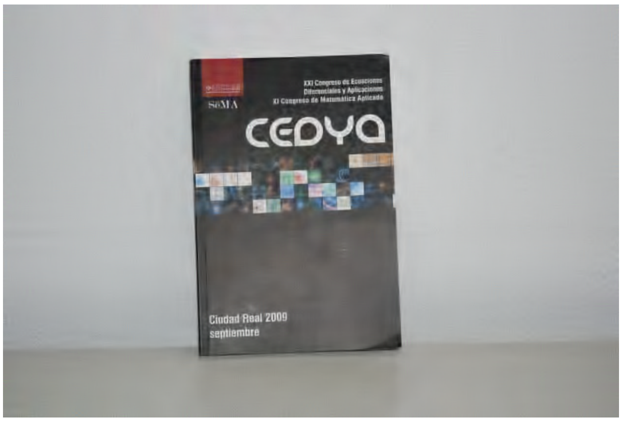
3.2.3. Multiscale recomposition factor

Images:

MS DST f = 0.3, PSNR = 33.8306dB



MS DST f = 0.6, PSNR = 33.7722dB



MS DST f = 0.8, PSNR = 33.6206dB

For lower f values the denoised image has less visible ringing artifacts and greater PSNR. This happens because of the DCT image pyramid which represents high frequencies which are the reason for the formation of ringing artifacts. Artifacts are caused by Gibbs' effect, so in order to ignore them we drop high frequencies. Therefore, when the factor is lower, we almost negate ringing artifacts.

To sum up, the presented in the paper algorithms have shown better results than the original DCT denoising. The main improvement can be seen not only in the increase of PSNR value but with ringing artifacts reducing, especially for MS DCT, and with better performance on flat areas of the image.