

Image Filtration Based on Principal Component Analysis and Nonlocal Image Processing: Algorithms and Applications

Andrey Priorov, Kirill Tumanov, Vladimir Volokhov
Department of Physics

P.G. Demidov Yaroslavl State University, Yaroslavl, Russia
andcat@yandex.ru, tumanov@susqu.edu, volokhov@piclab.ru

Abstract

The present paper is focused on the comparison of application results gathered from several algorithms based on Principal Component Analysis (PCA) and non-local processing. Its goal is to unveil the limitations, show best practices and make recommendations of use for each of the studied filtration schemes. Studied applications included filtration of an additive white Gaussian noise (AWGN) and a mixed noise from greyscale and colour images, and the removal of blocking artefacts from greyscale images.

Keywords: *image filtration, principal component analysis, non-local processing, comparison, applications.*

1. INTRODUCTION

Chatterjee and Milanfar in 2010, have shown that the theoretical limit of image reconstruction hasn't been yet achieved [2]. There still are debates on how to increase performance of filtration techniques used today. Among the widest spread methods of cancelling an AWGN in digital images, according to [7], are the algorithms which base on: local, non-local, pointwise and multipoint processing types.

The main problems with the quality of reconstructed images are: a Gibbs effect, which becomes highly noticeable on images containing objects with high brightness contrast on their outer edges, and an edge blurring of objects on an image being processed. Both of these effects highly degrade an image perception and the affected images do not suite for high demands. That is why in addition to their primary task contemporary filtration algorithms are generally required to reduce an impact of the named effects.

Algorithms taken for the study originally were implemented for AWGN filtration. However literature on digital images noise cancelling shows that modern AWGN filtration methods used for greyscale images may be successfully used in a series of other digital image processing tasks. Examples of such tasks are: colour image filtration, filtration of "raw" images, deletion of blurring from objects' edges, sharpening of objects' edges, etc.

Usage of the AWGN model may be explained with the help of statistics theory, namely – central limit theorem. It has an important practical value and may be interpreted to describe the work of devices containing numerous independent additive noise sources, each of which has its own random distribution, generally unknown. Resulting sum of these noise distributions is best described as a Gaussian distribution. On practice AWGN model well suits to simulate a thermal noise which is inevitably observed in digital components such as charge-coupled devices (CCDs) or CMOS matrixes.

2. USED FILTRATION SCHEMES DESCRIPTION

For the present study we took two similar methods which both used PCA and non-local processing approaches and a basic fundamental PCA method used in both of them.

2.1 Two-stage PCA filtration scheme

The most basic method used was the modification of two-stage PCA filtration scheme (Adaptive PCA + empiric Wiener filter (APCA+Wiener for short)).

The first processing stage forms a first "raw" evaluation $\hat{\mathbf{x}}^I$ of an unnoised image \mathbf{x} . After that, on the second processing stage, a "fine" evaluation $\hat{\mathbf{x}}^{II}$ of an unnoised image \mathbf{x} is formed based on the "raw" evaluation $\hat{\mathbf{x}}^I$, received after the previous stage.

We decided to test this filtration scheme along with two more advanced ones in order to see, how the latter two perform in comparison with the APCA+Wiener, which is one of their major components.

2.2 Sequential filtration scheme

First, as it was noted, this scheme includes an abovementioned APCA+Wiener filtration scheme as a base which forms an input for non-local denoising algorithm. The latter algorithm calculates the non-local means discussed previously [1]. As a result we receive a final non-local evaluation of the processed pixel $\hat{\mathbf{x}}^{II}(i, j)$ using the following formula:

$$\hat{\mathbf{x}}^{III}(i, j) = \sum_{k,l} g_{h^m}(i, j, k, l) \hat{\mathbf{x}}^{II}(k, l), \quad (1)$$

$$\text{where } g_{h^m}(i, j, k, l) = \frac{w_{h^m}(i, j, k, l)}{\sum_{k,l} w_{h^m}(i, j, k, l)}. \quad (2)$$

2.3 Parallel filtration scheme

The last method used in this work is a parallel filtration scheme based on the same algorithms which were used in the previous method.

Notable is that the "Two-stage PCA based filtration" block performs completely the same tasks that it does in a sequential scheme. On the other hand, contrary to the previous method, block "Non-local algorithm of image denoising" processes a noised image \mathbf{y} , not a second evaluation $\hat{\mathbf{x}}^{II}$ of an unnoised image \mathbf{x} . Wherein weight of a pixel $y(k, l)$ similar to a processed pixel $y(i, j)$ in a final evaluation $\hat{\mathbf{x}}^{III}$ of an unnoised image \mathbf{x} , received as an output of the block, is calculated using the formula:

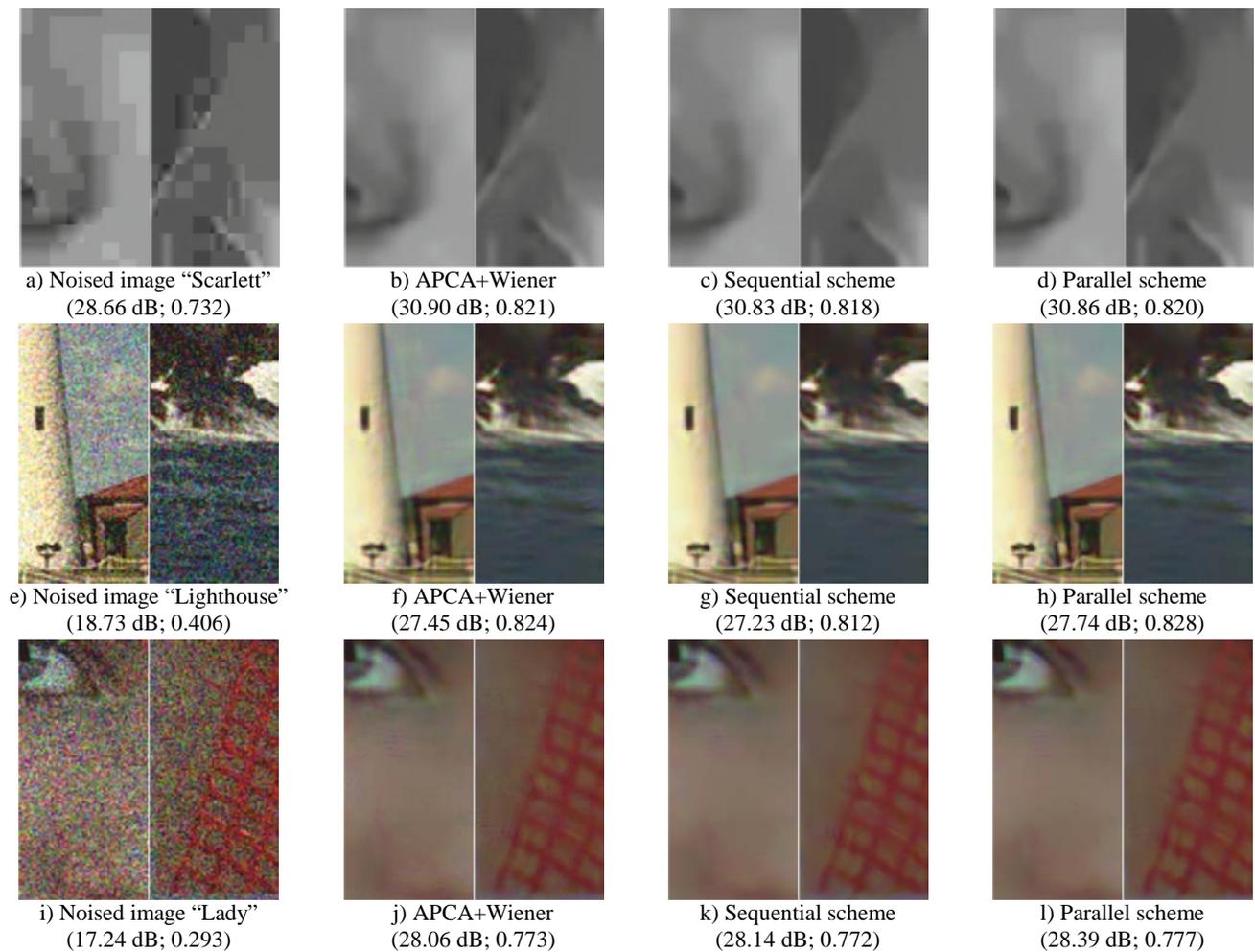


Figure 1: Examples of image reconstruction “Scarlett” ($Q = 5$, $\sigma = 25$), “Lighthouse” ($\sigma = 30$), and “Lady” ($\sigma_1 = 15$, $\sigma_2 = 0.2$) processed by APCA+Wiener, sequential and parallel filtration schemes. In brackets PSNR, dB and MSSIM

$$w_{h^{\text{III}}}(i, j, k, l) = \exp \left\{ - \frac{\sum_{m, n \in N} g_a(m, n) \cdot [\hat{x}^{\text{II}}(i+m, j+n) - \hat{x}^{\text{II}}(k+m, l+n)]^2}{(h^{\text{III}})^2} \right\}. \quad (3)$$

3. USAGE OF THE FILTRATION SCHEMES IN MODERN IMAGE PROCESSING TASKS

In this section we will show how the described AWGN filtration methods in addition to their primary use may be used for: (a) denoising AWGN-affected colour images; (b) filtration of mixed noises from greyscale images; (c) suppression of blocking artefacts in compressed JPEG images; (d) filtration of mixed noises from colour images.

3.1 Removal of blocking artefacts

The task was formulated as a situation where an image compression using JPEG algorithm is used as a noise model [5]. In this case a noise component \mathbf{n} may be treated as a result of distortion connected with blocking artefacts on a digital image. Then a solution to this task may be found as dispersion σ^2 of a

noise component \mathbf{n} . A possible way of finding σ^2 , using an *a priori* knowledge about a quantization matrix of JPEG standard coefficients, is shown in [4]. In this study search of σ^2 was performed manually.

For our experiments on blocking artefacts removal we used the same source of greyscale images [9]. We tested our algorithms on 256×256 pixels and 512×512 pixels images.

JPEG compression quality parameter Q was used to set the degree of compression, and σ^2 varied to demonstrate a dependence of the image reconstruction quality from the filtration smoothing parameter.

Notable is that the average increase rate for each algorithm was relatively low both on PSNR and MSSIM scales. Images compressed with $Q = 15$ after the processing with each of the algorithms were more damaged than reconstructed. Therefore it

can be concluded that neither of the studied algorithms may be applied to the JPEG compressed images with $Q \geq 15$. Although they remove blocking artefacts from the input image each of them gives a decrease in MSSIM value of a reconstructed image. This decrease is expressed in smoothing too much detail from test images and in most cases is considered unacceptable.

Special attention through all our further test analysis was devoted to the best performance results for each combination of variables and an algorithms' comparison based on this data.

Applying sequential filtration scheme to images with resolution higher than 256×256 pixels proved to be inadvisable because it showed lower average increase rates and it gave the least number of best reconstruction results both for PSNR and MSSIM. In addition it was observed that in higher resolution images the MSSIM decrease becomes more exponential and PSNR decreases linearly with the Q growth. However APCA+Wiener filtration scheme which showed the minimum number of best results for 256×256 pixels images performed much better on 512×512 pixels images and its average quality increase rates on average were better than the ones of sequential filtration scheme. This makes us consider the APCA+Wiener filtration method applicable for this task. On the other hand, parallel scheme strengthened its positions among the compared algorithms.

Results of JPEG compressed greyscale digital images filtration with the discussed filtration schemes are visualised on Figure 1 on example of "Scarlett" 512×512 pixels image. Hereinafter only fragments of images are shown for easier comparing.

It can be concluded that all the named filtration methods may be successfully applied to the task of removal of blocking artefacts with the notion to the listed limitations, however the reconstructed images quality shows to be relatively low and thus a further research in this area is needed.

3.2 AWGN-affected colour images filtration

The task is of especially current interest from the standpoint of modern applications. That is why numerous solutions have been formulated to perform it. The one we used in the present work is a direct channelwise processing of an RGB image. For simplicity we did no transfer from RGB images to images with separated colour and brightness information [4]. AWGN was added to each channel independently with the same characteristics. Relevancy of use of the described noise model may be confirmed with the presence of image capture systems which consist of three separate CCDs or CMOS matrixes. This method was used for simplicity and for further research it may be extended by using specific noise models and applying them to each image layer in a variation of interest.

For this test we used 768×512 pixels colour images from the CIPR's Kodak image database [8]. We used AWGN with σ values in a range from 15 to 25.

Notable is the fact that through our entire test series sequential scheme never showed a best performance neither in PSNR nor in MSSIM. This enforces our proposal of use the parallel filtration scheme with its approach of using two independent evaluations of an unnoised image \mathbf{x} . It should also be mentioned that APCA+Wiener filtration scheme showed very competitive results in terms of MSSIM. This scheme even outperformed the parallel scheme for AWGN with $\sigma = 30$. That is why this scheme

may be of use when a "good" instead of "excellent" colour images filtration results are needed.

All the compared filtration methods provide a high-quality processing of main objects' edges. This fact shows its results in this test series – absolute values of PSNR and MSSIM decrease, but carefully processed edges slow this decrease for MSSIM.

Applying sequential filtration scheme to the task of colour images filtration proved to be infeasible as well as for the removal of blocking artefacts. At the same time parallel scheme showed almost absolute best performance in this task, especially according to PSNR quality assessment of the reconstructed images.

Results of AWGN-affected colour digital images filtration with the named filtration schemes are visualised on Figure 1 on example of "Lighthouse" 768×512 pixels image.

It can be concluded that APCA+Wiener and parallel filtration methods may be successfully applied to the task of AWGN-affected colour images filtration. Quality of the reconstructed images for these methods is rather high, although on high-resolution colour images the smoothing effect, which arises after filtration procedures, becomes more visible, due to the superposition of different image layer filtration defects. The smart way of layers integration may be of good help in solving the issue, and its implementation requires an additional study.

3.3 Mixed noise images filtration

The discussed AWGN model may be complicated by a usage of mixed noise model. An example of such model was proposed by Hirakawa and Parks in 2006 [6] to characterize noise of CMOS matrixes. The model may be described as follows:

$$\mathbf{y} = \mathbf{x} + (\sigma_1 + \sigma_2 \mathbf{x})\mathbf{n}, \quad (4)$$

Where σ_1 and σ_2 – are the constants which determine a noisiness degree, and \mathbf{n} – is an AWGN with zero mean and $\sigma = 1$. If $\sigma_2 = 0$ this noise model transforms into the described earlier AWGN model.

Because of the irregular character of noise dispersion in the mixed noise model, which is explained by the dependency of noise from the initial signal, a direct application of the described schemes is impossible. For this reason we used a generalized homomorphic filtration method [3], proposed by Ding and Venetsanopoulos in 1987. The idea of this method is in using a logarithm-type transform to interpret noised data \mathbf{y} as a sum of an initial unnoised signal and AWGN, process them with described filtration schemes and then reconstruct the data with the inverse transform.

For this test we used all the mentioned above images - 256×256 and 512×512 pixels greyscale and 768×512 pixels colour images from [8,9]. We used a mixed noise with σ_1 values in a range from 15 to 25 and σ_2 values in a range from 0.1 to 0.3.

The parallel filtration scheme showed best results of image reconstruction on a PSNR scale in a prevailing number of tests. However, MSSIM quality assessment results were almost equally distributed between all three filtration schemes. This may be explained by the fact that the MSSIM values are formed based on evaluating the image, which colour layers were processed independently, so that each scheme at the end formed a synergetic reconstructed image.

Although sequential filtration scheme showed nearly as many best results as parallel scheme on MSSIM scale for 256×256 pixels greyscale images, application of the sequential filtration scheme to this task is infeasible for the higher resolution images and colour images.

PSNR and MSSIM increase for correlating pairs of results is almost linear. All the compared filtration methods provide a high-quality processing of main objects' edges and filtration quality in general.

Results of mixed noise affected colour digital images filtration with the discussed filtration schemes are visualised on Figure 1 on example of "Lady" 768×512 pixels image.

Application of all three algorithms to images affected by this noise model on high levels of σ_1 and σ_2 resulted in visible colour changes of minor image details and objects. For example, on a "Caps" colour image several little clouds previously of a white colour were reconstructed as red-like, because of the high number of red noise pixels on an input noised image. We consider this type of reconstruction defects significant as they are easily noticeable, and we understand that for a successful use of the discussed filtration schemes to the mixed noise filtration on colour images some additions to the algorithms need to be made. However the overall quality of reconstructed images which were noised with $\sigma_2 = \{0.1, 0.2\}$ is high and the defects described above are unnoticeable. That is why it can be concluded that APCA+Wiener and parallel filtration methods may be successfully applied to the task of mixed noise affected greyscale and colour images filtration with limitation in using the high σ_2 values for colour images.

4. COMPARISON OF THE USED FILTRATION METHODS

Here we give a brief discussion on the filtration schemes performance in the described digital image processing applications.

4.1 Modification of the two-stage PCA filtration scheme

The most advantageous feature of this method is its low computational cost and construction simplicity.

Primary disadvantages of using this filtration scheme from the standpoint of reconstructed images quality are: (1) substantial amount of ringing artefacts on image objects' edges, this effect is especially visible on high-contrast image parts (see Figure 1); (2) high blurring of image objects' edges, compared to other modern filtration methods [4].

4.2 Sequential filtration scheme

Advantages of this method are in its relative construction and implementation simplicity and the decrease of the amount of ringing artefacts on image objects' edges (see Figure 1).

Primary disadvantages of using this filtration scheme are in the presence of high blurring of image objects' edges and high computational cost of the filtration algorithm.

4.3 Parallel filtration scheme

Advantages of this method are: (1) high quality of the reconstructed images both on PSNR and MSSIM scales; (2) minimal amount of ringing artefacts on image objects' edges, and low blurring of image objects' edges (see Figure 1).

Primary disadvantage of using this filtration scheme is in the high computational cost of the filtration algorithm.

5. CONCLUSION

Our study has shown how different digital image filtration algorithms based on the PCA and non-local processing may be applied to modern digital image processing tasks. Experimental results obtained prove the idea of successful application of these filtration methods to the removal of blocking artefacts, AWGN- and mixed noise affected image filtration. In the present work we listed the limitations of use for each method and proposed approaches of their overcome. Results of other contemporary state-of-the-art filtration algorithms are not provided due to the absence of relevant experimental data. A thorough comparison may be a topic of our further investigation.

6. AKNOLEDGMENTS

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About the author

The authors are with P.G. Demidov Yaroslavl State University, Yaroslavl, Russia. (email: andcat@yandex.ru; tumanov@susqu.edu; volokhov@piclab.ru).