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Denoising of image using bilateral filtering in multiresolution

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Abstract

One of the very efficient and resource conservative image processing methodology is with the help of bilateral filters. This technique filters the image without the help of edge smoothing but it does employs spatial averaging in a non-linear way. The filtering technique discussed above is very much dependent on the parameters of its filters. A very slight change in filter parameter values effects the outputs and results in a most drastic manner. In this paper, the author has worked on two contributions. In the applications concerning image denoising, the author has contributed in study of the parameter selection of bilateral filters which are optimal in nature. The contribution number two is about extending the present work i.e. extension of the filters which are bilateral in nature. In this process, the bilateral filtering of images is applied to the lower frequency sub-bands which is also known as approximation sub-band. This sub-band is obtained by using the wavelet transformations. Hence, a new framework for image denoising will be created which will be combination of multiresolution bilateral filtering and wavelets transformation techniques. As a matter of fact, this combination is efficient in contradicting noise from an image.

Keywords: biletaral filters, image denoising, wavelet transform

1. Introduction

Digital data, more preciously digital images, are prone to noise from so many different sources. Display of characteristics which are non-uniformly spatial in nature are shown by some of the noise components such as dark signal non-uniformity aka DSNU or photo-response non-uniformity (PRNU). Because of the reason that the spatial pattern of the above mentioned noise does not vary with time, the noise is sometimes referred to as fixed pattern noise (FPN). This contrasts with the temporal noise, where the noise does not happen to have a fixed pattern. Some of the examples of temporal noise are reset noise, read noise, photon shot noise and dark current. Well there are many other characteristic as well which determines the noise, these factors includes type of sensors in the image capture device, dimensions of the pixel, temperature, time of exposure, and speed of ISO. In the most general form, the digital noise varies with space and dependent on the channel. As we know that the blue filters has got the lowest transmittance, blue colored channel is generally the nosiest of all. One of the very much neglected characteristic of digital noise in images is its spatial frequency. Shown in Figure 1, we can actually see the high-frequency aka fine-grain and low-frequency aka coarse grain fluctuations. It is comparatively easier to remove the noise which is of high frequency. Whereas it becomes very difficult to get hold of difference between the original message/image signal and a low frequency noise.

Over the course of time, there have been multiple image denoising methods developed and researched upon. The most popular methods of all is undoubtedly the use of wavelet transformation and thresholding. As per the official definition of wavelet thresholding, the signal under processing is decomposed into two components. The first one being approximation coefficients of the data, which is also known as low-frequency components. The second one is its detailing coefficients which is also known as high-frequency components. Now, the most part of image information is stored in the large coefficients which is easier to denoise. Problematic area is denoising the detail sub-bands. This denoising is done by wavelet thresholding operation. Hence wavelet thresholding operation is the key element of image denoising via wavelets. There are a number of threshold strategies being researched, popular ones being VisuShrink [1], SureShrink [2] and BayesShrink [3]. In the first one, which is VisuShrink approach, the threshold is calculated which act universally on the noisy data. This threshold is actually a function of noise variance, however the number of samples is created using the error measure of minimax approach. In the second one, which is SureShrink thresholding approach, it works in relation with the risk estimator as

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proposed by Stein. In the final one, which is Bayesian thresholding, the value of the threshold is determined in the bayesian framework. These were some of the commonly used thresholding methods in wavelet thresholding. However, with the course of time the above mentioned methodologies have been improved by various methods, common ones being the correlation of wavelet coefficients at the interscale and intrascale level [4-8].

Figure 1. Image and its red, green and blue channels.

One of the most recent methods which is also quite popular now is bilateral filter [9-16]. The basic methodology behind working of this filter is that is focuses on a local neighborhood of pixels and takes its weighted sum. The calculation of weights depends upon the intensity distance and spatial distance. This is a very good method as it preserves all the edges of the image data but on the other hand noise present in that local neighborhood gets leveled/averaged out. There have been a lot of recent papers/journals which have actually connected the technique of multiresolution bilateral filtering with a lot another well established and tested techniques. In [17-20], it is very well mentioned that with the help of a extremely specific cost function the initial iteration of the algorithm of Jacobi is exactly similar to the bilateral filtering. Papers like [21] and [22] states that bilateral filters and anisotropic diffusion are similar in nature. So far we have talked about the applications of bilateral filtering on only image denoising domain, but that is not the only domain it works with. There are many other applications where bilateral filtering is being used. Retinex [23-35], image enhancements [31], volumetric denoising [29] etc. are some of them. The parameter selection for bilateral filtering is pretty much a method of hit and trial. In the next section (i.e. section II) the author has talked about selection of parameters for bilateral filtering. The proposed extension to bilateral filters is presented in section III.

2. Bilateral Filter's Parameter Seletion

It is evident from [1] that the two essentials parameters to be used in bilateral filtering are intensity domain and spatial domain. The topic of selecting appropriate value for these parameters have not been answered properly while talking in theory. The paper [22] finds out the first derivative of the signal and then checks out its behavior as compared to intensity domain by spatial domain values. Another method was discussed in [26] where the author hypotheses for a non-local means algorithm a method which is adaptive in nature along with neighborhood size selection. The size of the neighborhood is chosen such that the upper bound of local L2 risk is coming out to be bare minimum. But the thing to be noted here is that effect of intensity domain is not taken into consideration. This section of the paper is to deal with the presentation of the study (which would be empirical in nature) of the parameter values and setting them up to an optimal range. These parameter values will be function of the noise variance. We might also see that

the first parameter i.e. intensity domain parameter is much more important at criticality then spatial domain parameter.

In this section, we will demonstrate the experiment which was done to understand the relationship between domain parameter, spatial parameter and the noise standard deviation. We started with some test images and added zero mean white Gaussian noise to them. Then we apply our bilateral filter on this noisy image in which we just added the noise. This bilateral filter was applied on varied values of domain parameter and spatial parameter. Also, this very experiment was done multiple times, again with varied values of noise variances and based on that multiple MSEs (mean squared value) were observed and noted. The experiment shows that the optimal value of spatial domain parameter does not change very much with the level of noise variance. However, when we compare the optimal value of intensity domain parameter, it does changes more than the previous parameter. On further calculations in the experiment, it was seen that a better range for spatial domain parameter is approximately 1.5-2.1. But the optimal value of intensity domain parameter changes drastically when the standard deviation of noise changes. The result is very much expected because the numerical value of intensity domain parameter is much smaller than the spatial domain parameter. Because of which the noisy data remains untouched, just like in the case of salt and pepper noise problem as seen in bilateral filter [16]. When intensity domain parameter is large enough, spatial domain parameter becomes important. We should note that the value of spatial domain parameter should not be increased too much, It might result in over-smoothing of the noisy area and this will lead to decrease in MSE value.

3. Framework for Multiresolution Denoiding of Noisy Image

As it is already discussed above in first section, only white noise does not exist in images, it may happen that the noise have many different spatial frequencies (fine grain and coarse grain). In various research papers, analyzing noisy images via multiresolution analysis has proved to be an important and efficient tool for removing noise. It makes it easier to separate image with noisy pixels. The image shown in Figure 2 is evident enough to use the bilateral filtering technique in multiresolution framework. In the image, we can see the approximate sub-bands of a noisy image. The image also shows the transformation of coarse grain noise into fine grain noise when the image is decomposed into its sub-bands. This also shows that we can get rid of the coarse grain noise at lower level of sub-band.
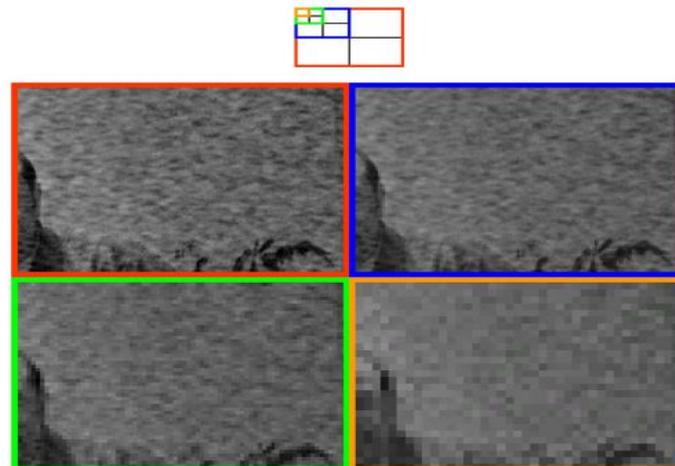

Figure 2. Multiresolution properties of a coarse grain noise

The proposed framework as suggested by the author is shown in Figure 3. We make use of wavelets decomposition method using which a signal is then decomposed into its frequency sub-bands. Before reconstructing the signal back, we apply bilateral filtering into the approximation sub-band. This advanced filter is now capable of removing low-frequency noise components, very different than the standard single-level bilateral filter [16]. To sum the whole process, bilateral filters works in the approximation sub-band area and in this area some noise components can be identified and removed in an

effective manner. Hence the new denoising concept combines two very efficient methods namely wavelet decomposition and bilateral filtering technique.
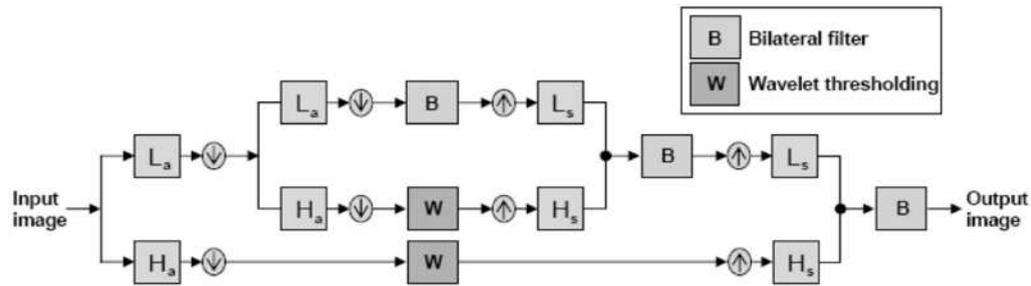

Figure 3. Proposed methodology

4. Results and Discussion

Experiments were performed on the proposed scenario to check the efficiency and effectiveness of the scheme. To get the desired output, we picked few images and added noise to them. Then these images were denoised using the proposed scheme. Figure 4 shows all the noisy images and their denoised counterparts.
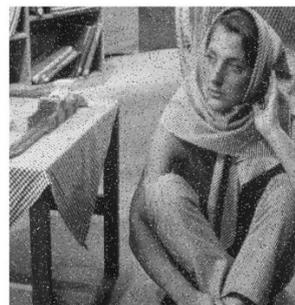
Noisy image: salt and pepper noise   Denoised image: salt and pepper noise

Noisy image: gaussian noise   Denoised image: gaussian noise

Noisy image: poisson noise   Denoised image: poisson noise

Noisy image: speckle noise   Denoised image: speckle noise
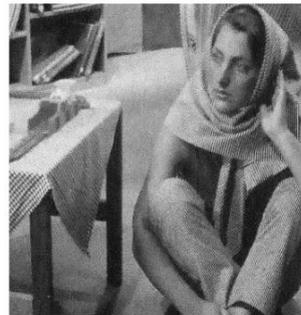
Noisy image: salt and pepper noise   Denoised image: salt and pepper noise

Noisy image: gaussian noise   Denoised image: gaussian noise

Noisy image: poisson noise   Denoised image: poisson noise

Noisy image: speckle noise   Denoised image: speckle noise

Noisy image: salt and pepper noise   Denoised image: salt and pepper noise

Noisy image: gaussian noise   Denoised image: gaussian noise

Noisy image: poisson noise   Denoised image: poisson noise

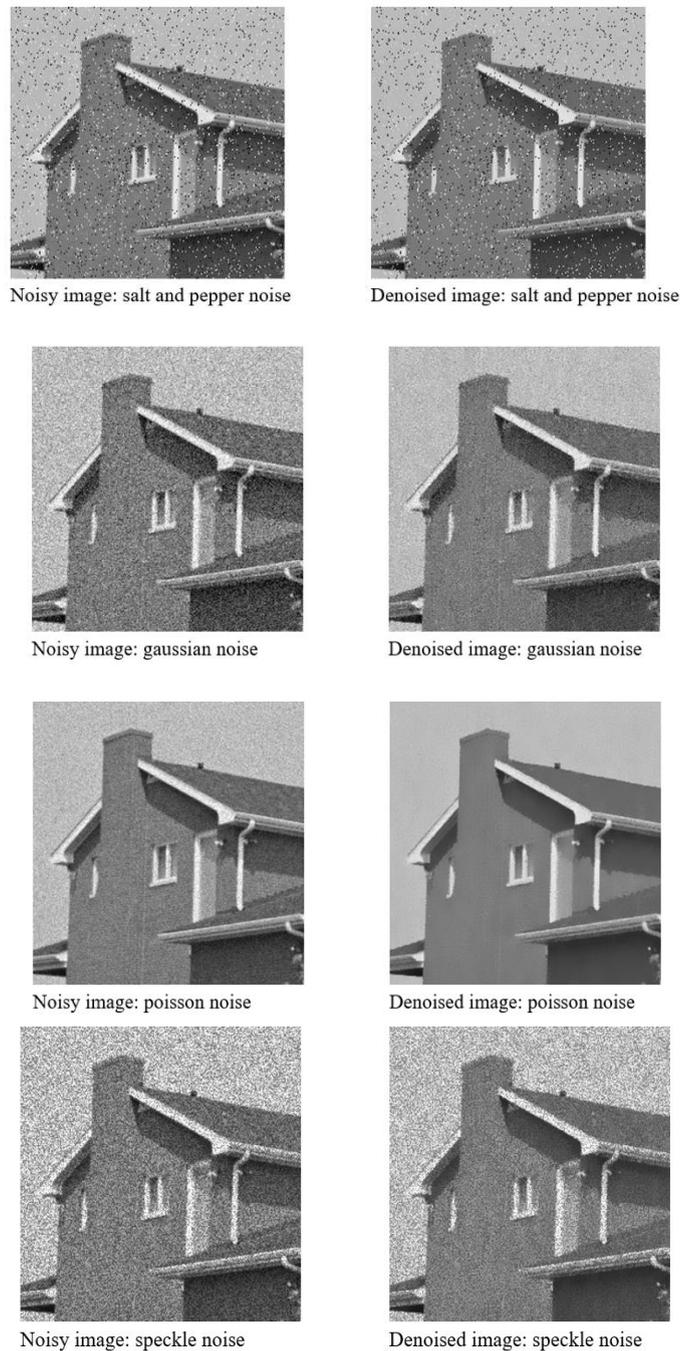Noisy image: speckle noise   Denoised image: speckle noise

Figure 4. the noisy images and their denoised counterparts

5. Conclusion and Future Work

In this paper, the main focus of the computation was on optimal value of the parameters that are to be used for bilateral filtering, with image denoising being the main application. This would present a framework with multiresolution image denoising, not to forget that this scheme is an amalgam of wavelet processing and bilateral filtering.

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