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IMAGE DE-NOISING USING VARIOUS WAVELET SCHEMES

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ABSTRACT

An image may be defined as a two-dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of **f** at any pair coordinates (x, y) is called the intensity or gray level of the image at that point [2][4]. When (x, y) and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. In this paper a proposed approach is defined and it is compared with different approaches of image de-noising. The proposed approach shows the best results as compare to the existing approaches.

Keywords: Image, De-Noise, PSNR, MSE, RCRS.

I. INTRODUCTION

Classification of De-noising Algorithms

There are two basic approaches to image de-noising, spatial filtering methods and transform domain filtering methods.

Spatial Filtering

A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters.

(a) Non-Linear Filters

With non-linear filters, the noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in picture sin visible. In recent years, a variety of nonlinear median type filters such as weighted median [8], rank conditioned rank selection (RCRS) [9], and relaxed median (RM) [10]have been developed to overcome this drawback.

(b) Linear Filters

A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error.

Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise. The wiener filtering [11] method requires the information about the spectra of the noise and the original signal and it works well only if the underlying signal is smooth.

Types of Noises

We discuss noise commonly present in an image. Note that noise is undesired information that contaminates the image .In the image de-noising process; information about the type of noise present in the original image plays a significant role. Typical images are corrupted with noise modelled with either a Gaussian, uniform, or salt or pepper distribution. Another typical noise is a speckle noise, which is multiplicative in nature.

Noise is present in an image either in an additive or multiplicative form [Im01]. An additive noise follows the rule.

w(x,y)=s(x,y)+n(x,y),

w(x,y)= s(x,y)*n(x,y),

Where (x,y) is the original signal ,n(x,y) denotes the noise introduced in to the signal to produce the corrupted image w(x,y), and (x,y) represents the pixel location. Image additional so find is application sin image morphing [Um98]. By image multiplication, we mean the brightness of the image is varied.

The digital image acquisition process converts an optical image into a continuous electrical signal that is then sampled [Um98]. At every step in the process there are fluctuations caused by natural phenomena, adding a random value to the exact brightness value for a given pixel.

Noise in an image is a very common problem. An image gets corrupted with different types of noise during the processes of acquisition, transmission/ reception, and storage/ retrieval. Noise may be classified as substitutive noise (impulsive noise: e.g., salt & pepper noise, random-valued impulse noise, etc.) and additive noise (e.g., additive white Gaussian noise). The impulse noise of low and moderate noise densities can be removed easily by simple de-noising schemes available in the literature

The simple median filter [34] [1] [6] works very nicely for suppressing impulse noise of low density. However, now-a-days, many de-noising schemes [13] are proposed which are efficient in suppressing impulse noise of moderate and high noise densities. In many occasions, noise in digital images is found to be additive in nature with uniform power in the whole bandwidth and with Gaussian probability distribution. Such a noise is referred to as Additive White Gaussian Noise (AWGN).It is difficult to suppress AWGN since it corrupts almost all pixels in an image. The arithmetic mean filter, commonly known as Mean filter can be employed to suppress AWGN but it introduces a blurring effect.

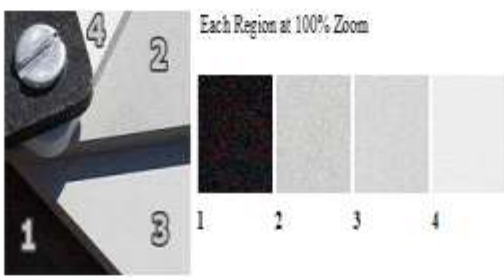


Figure 1.1: Image Suppression due to different noises

Noise not only changes depending on exposure setting and camera model, but it can also vary within an individual image. For digital cameras, darker regions will contain more noise than the brighter regions; with film the inverse is true. Note how noise becomes less pronounced as the tones become brighter. Brighter regions have a stronger signal due to more light, resulting in a higher overall PSNR. This means that images which are underexposed will have more visible noise — even if you brighten them up to a more natural level afterwards. On the other hand, overexposed images will have less noise and can actually be advantageous, assuming that you can darken them later and that no region has become solid white where there should be texture. Noise is also composed of two elements: fluctuations in color and luminance. Color or "chroma" noise is usually more unnatural in appearance and can render images unusable if not kept under control. The example below shows noise on what was originally a neutral grey patch, along with the separate effects of chroma and luminance noise.

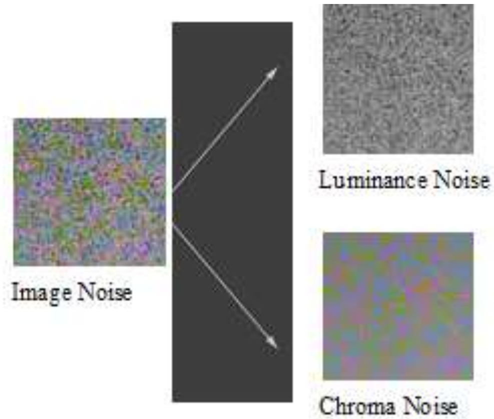


Figure 1.2: Different types of noises

The relative amount of chroma and luminance noise can vary significantly from one camera model to another. Noise reduction software can be used to selectively reduce both chroma and luminance noise, however complete elimination of luminance noise can result in unnatural or "plasticy" looking images.

Noise fluctuations can also vary in both their magnitude and spatial frequency, although spatial frequency is often a neglected characteristic. The term "fine-grained" was used frequently with film to describe noise whose fluctuations occur over short distances, which is the same as having a high spatial frequency. The example below shows how the spatial frequency can change the appearance of noise.

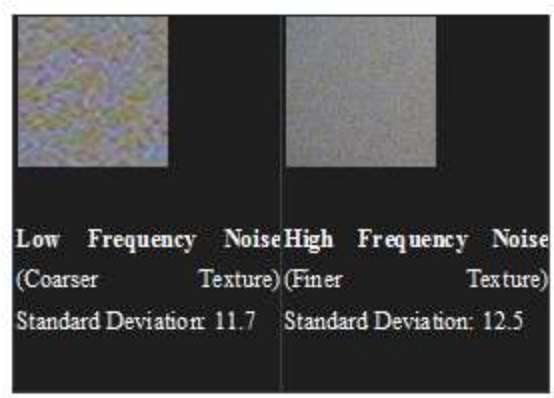


Figure 1.3: Effect of Standard deviations on frequency of different texture

If the two patches above were compared based solely on the magnitude of their fluctuations (as is done in most camera reviews), then the patch on the right would seem to have higher noise. Upon visual inspection, the patch on the right actually appears to be much less noisy than the patch on the left.

This is due entirely to the spatial frequency of noise in each patch. Even though noise's spatial frequency is under emphasized, its magnitude still has a very prominent effect. The next example shows two patches which have different standard deviations, but the same spatial frequency.

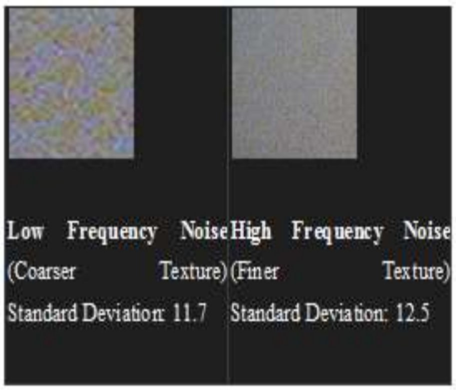


Figure 1.4: Effect of Standard deviation on magnitude of different texture

Note how the patch on the left appears much smoother than the patch on the right. High magnitude noise can overpower fine textures such as fabric or foliage, and can be more difficult to remove without over softening the image. The magnitude of noise is usually described based on a statistical measure called the "standard deviation," which quantifies the typical variation a pixel will have from its "true" value. This concept can also be understood by looking at the histogram for each patch if each of the above patches had zero noise, all pixels would be in a single line located at the mean. As noise levels increase, so does the width of this histogram. We present this for the RGB histogram, although the same comparison can also be made for the luminosity and individual color histograms. Efficient suppression of noise in an image is a very important issue. De-noising finds extensive applications in many fields of image processing. Image de-noising is usually required to be performed before display or further processing like texture analysis [15] [13], object recognition, image segmentation [11], etc.

Select noise magnitude: LO W HIG H

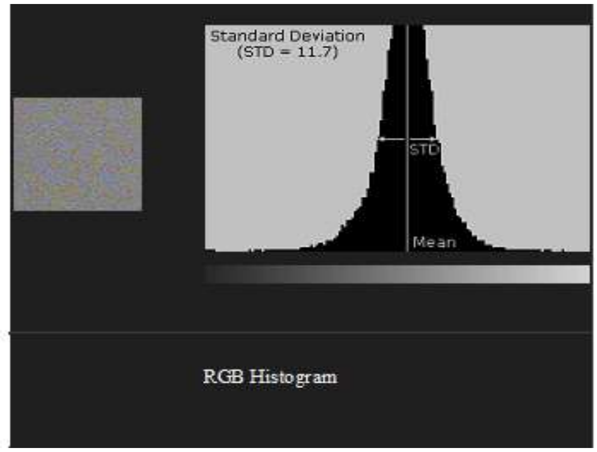


Figure 1.5: Histogram curve of standard deviation

Conventional techniques of image de-noising using linear and nonlinear techniques have already been reported and sufficient literature is available in this area. Recently, various nonlinear and adaptive filters have been suggested for the purpose. The objectives of these schemes are to reduce noise as well as to retain the edges and fine details of the original image in the restored image as much as possible. However, both the objectives conflict each other and the reported schemes are notable to perform satisfactorily in both aspects. Hence, still various research workers are actively engaged in developing better filtering schemes using latest signal processing techniques.

IMAGE METRICS

a) MSE is defined as:

$$\mathbf{MSE} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}[\hat{f}(x,y) - f(x,y)]^2}{MxN}$$

b) The MAE is defined as:

$$\mathbf{MAE} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}[\hat{f}(x,y) - f(x,y)]}{MxN}$$

c) PSNR is defined as:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{1}{\mathrm{MSE}}\right)\mathrm{dB}$$

Results for Speckle Noise with standard deviation σ= 0.4 for Lena


(a)


(b)


(c)


(d)


(e)


(f)


(g)


(h)


(i)

Figure 1.6: Results for image "Lena" Noise type= Speckle and standard deviation (σ)=0.03 (a) Original image of Lena(256*256) (b) Noisy Image of Lena(256*256) (c) De-noised of "Lena" by Donoho Soft Thresholding (d) De-noised of "Lena" by Donoho Hard Thresholding (e) De-noised of "Lena" by Wavelet Thresholding (f) De-noised of "Lena" by (g) De-noised of "Lena" by Bayes Shrinkage (h) De-noised of "Lena" by BLS-GSM De-Noising (i) De-noised of "Lena" by Proposed Method.

It is very clear from the above figures that there is change in the quality of image after de-noising with the proposed method over the existing techniques. This represents the improvement in the objective quality of the image. The proposed approach is tested and implemented over the existing techniques as Donoho Soft Thresholding, De-Noised by Donoho Hard Thresholding , De-noised by Wavelet Thresholding , De-Noised by Basian Thresholding, De-noised by Bayes Shrinkage, De-noised by BLS-GSM by (BLS De-Noising), De-noised by Proposed Approach.

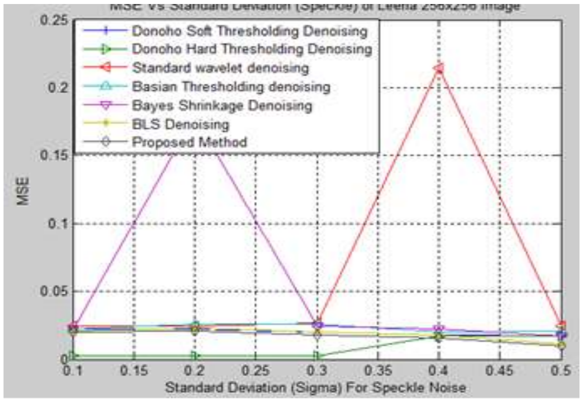
So we conclude the proposed approach gives the significant results over the existing techniques.

MSE Vs Noise Variance (Sigma) of Speckle

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Wavelet Thresholding	BasianThresh olding	Shrinkage De-noising	BLS Denoising	Proposed
1	0.01	0.0221	0.0024	0.0244	0.022	0.0224	0.02101	0.0202
2	0.02	0.022	0.0024	0.0247	0.0256	0.1789	0.0229	0.021
3	0.03	0.02	0.0026	0.0268	0.0259	0.02458	0.0199	0.0176
4	0.04	0.0179	0.0169	0.2147	0.0204	0.02244	0.0179	0.0154
5	0.05	0.0174	0.0174	0.0247	0.0211	0.0173	0.0113	0.0101

Noise for Lena (256x256) image

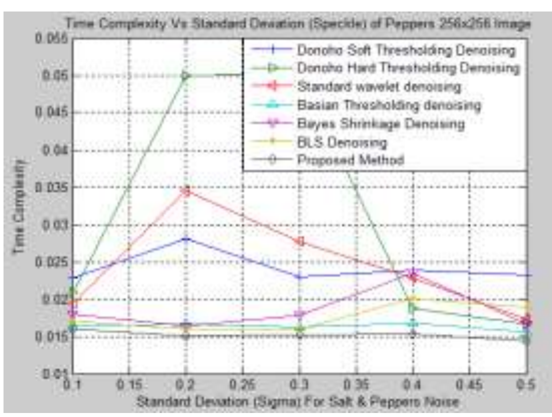
Table 1.1: MSE for Lena with Speckle Noise



Graph 1.2 Execution time (sec.) Vs. Noise variance (Sigma) for Peppers image with Salt & Peppers Noise

Sr. No	Noise Variance (σ)	Donoho Soft Thresholding	Donoho Hard Thresholding	Standard Wavelet Thresholding	BasianThresholding	Bayes Shrinkage Denoising	BLS Denoising	Proposed
1	0.1	0.022884	0.020804	0.019375	0.016347	0.017927	0.017093	0.01601
2	0.2	0.028031	0.05	0.034593	0.016641	0.016402	0.016042	0.015047
3	0.3	0.022965	0.050182	0.027666	0.016264	0.017836	0.015998	0.015257
4	0.4	0.02386	0.018694	0.022852	0.016751	0.023427	0.020069	0.015362
5	0.5	0.023209	0.016611	0.017284	0.015657	0.01666	0.018819	0.014353

Table 1.2: Execution Time for Peppers with Salt & Peppers Noise



Graph 1.2: Time Complexity for Peppers with Salt & Peppers Noise

II. CONCLUSION

It has been observed that BayesShrink is not effective for noise variance higher than 0.05. De-noising salt and pepper noise using proposed method has proved to be efficient due to adaptive median filter used in it. When the noise characteristics of the image are unknown, de-noising by multi fractal analysis has proved to be the best method. It does a good job in de-noising images that are highly irregular and are corrupted with noise that has a complex nature. In the two methods considered, namely multi fractal regularization and multi fractal pumping, the second method produces visually high quality images. Besides, the complexity of the algorithms is measured according to the CPU computing time flops. This can produce a time complexity standard for each algorithm Since selection of the right de-noising procedure plays a major role, it is important to experiment and compare the methods.

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