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AN INVESTIGATION INTO THE DIFFERENT IMAGE DE-NOISING TECHNIQUES

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ABSTRACT

Transmission of visual information in the modern age as images and videos has become an easy and a widely used method of communication. Therefore the importance of efficient and adequate image processing has increased many folds in today's time. The digital images often get corrupted during transmission due to misinterpretation of bits and we get an image with falsified or unclear information which we call a noisy image. This manipulation in the original digital image is nothing but the noise. This image needs processing to filter out the noise from image. This process is called Image De-noising. There are different techniques to remove the noise from an image. In this paper we review these techniques, such as filtering techniques (linear and non linear filters), wavelet transform based approach and multifractal analysis, and perform a comparative study of these techniques. First, we will see the different noise models into which the noise can be classified. Prior information about the type of noise helps in choosing the right filtering technique for that noise type. Different noise models have been studied in this paper namely Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. We found that the filtering approach is best suitable for images corrupted with Salt and pepper noise, wavelet transform based approach is best suitable for images corrupted with Gaussian noise and for other complex noise characteristics, multifractal analysis can be used. We have also compared the Signal to Noise ratio of the images to compare the performance of the different image de-noising techniques.

Keywords: Image Denoising, Filters, Noise, Wavelet, Multifractal

I. INTRODUCTION

In this digital age, digital images play a very important role to carry and convey useful information. In our daily life digital image find its application in satellite television, medical images like MRI (magnetic resonance imaging), ultrasound images and x-ray images etc, astronomy, geographical information system and computer tomography. Data collected and put together from image sensors forms a digital image. This data set collected by image sensors gets contaminated with noise due to the imperfect instruments, problem during data acquisition process and due to the natural phenomena. The data set may also get corrupted with noise due to transmission errors and compression.

Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained [1]. Degradation comes from blurring as well as noise due to electronic and photometric sources. Blurring is a form of bandwidth reduction of the image caused by the imperfect image formation process such as relative motion between the camera and the original scene or by an optical system that is out of focus [2]. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contributes to the degradation.

Let us now consider the representation of a digital image. A 2-dimensional digital image can be represented as a 2-dimensional array of data s(x,y), where (x,y) represent the pixel location. The pixel value corresponds to the brightness of the image at location (x,y). Some of the most frequently used image types are binary, gray-scale and colour images [3].

Binary images are the simplest type of images and can take only two discrete values, black and white. Black is represented with the value ‘0’ while white with ‘1’. Note that a binary image is generally created from a gray-scale image. A binary image finds applications in computer vision areas where the general shape or outline information of the image is needed. They are also referred to as 1 bit/pixel images. Gray-scale images are known as monochrome or one-colour images. The images used for experimentation purposes in this paper are all gray-scale images. They contain no colour information. They represent the brightness of the image. This image contains 8 bits/pixel data, which means it can have up to 256 (0-255) different brightness levels. A ‘0’represents black and ‘255’ denotes white. In between values from 1 to 254 represent the different gray levels. As they contain the intensity information, they are also referred to as intensity images.

Colour images are considered as three band monochrome images, where each band is of a different colour. Each band provides the brightness information of the corresponding spectral band. Typical colour images are red, green and blue images and are also referred to as RGB images. This is a 24 bits/pixel image.

There are various methods to help restore an image from noisy distortions. Selecting the appropriate method plays a major role in getting the desired image. The de-noising methods tend to be problem specific. For example, a method that is used to de-noise satellite images may not be suitable for de-noising medical images. In order to quantify the performance of the various de-noising algorithms, a high quality image is taken and some known noise is added to it. This would then be given as input to the de-noising algorithm, which produces an image close to the original high quality image. In case of image de-noising methods, the characteristics of the degrading system and the noises are assumed to be known beforehand. The image s(x,y) is blurred by a linear operation and noise n(x,y) is added to form the degraded image w(x,y). This is convolved with the restoration procedure g(x,y) to produce the restored image z(x,y).

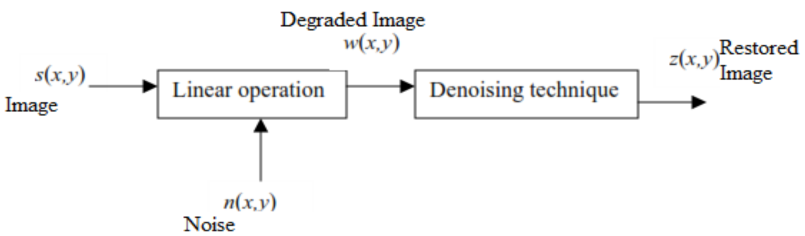

Figure 0.1: Denoising Concept.

The “Linear operation” shown in Fig. 1.1 is the addition or multiplication of the noise n(x,y) to the signal s(x,y). Once the corrupted image w(x,y) is obtained, it is subjected to the de-noising technique to get the de-noised

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image z(x,y). The point of focus in this paper is comparing and contrasting several "de-noising techniques" (Fig. 1.1).

Three popular techniques are studied in this paper. Noise removal or noise reduction can be done on an image by filtering, by wavelet analysis, or by multifractal analysis. Each technique has its advantages and disadvantages. De-noising by wavelets and multifractal analysis are some of the recent approaches. Wavelet techniques consider thresholding while multifractal analysis is based on improving the Holder regularity of the corrupted image.

II. DIFFERENT NOISE TYPES

Typical images are corrupted with additive noises modelled with either a Gaussian, uniform, or salt and 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. An additive noise follows the rule:

$$w(x,y) = s(x,y) + n(x,y) \quad (0.1)$$

While the multiplicative noise satisfies:

$$w(x,y) = s(x,y) \times n(x,y) \quad (0.2)$$

Where s(x,y) is the original signal, n(x,y) denotes the noise introduced into the signal to produce the corrupted image w(x,y), and (x,y) represents the pixel location. The above image algebra is done at pixel level. Image addition also finds applications in image morphing [3]. By image multiplication, we mean the brightness of the image is varied.

2.1 Gaussian Noise

Gaussian noise is evenly distributed over the signal [3]. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function given by:

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2} \quad (0.3)$$

Where g represents the gray level, m is the mean or average of the function, and σ is the standard deviation of the noise. Graphically, it is represented as shown in Fig. 2.1. When introduced into an image, Gaussian noise with zero mean and variance as 0.05 would look as in Fig. 2.2. Fig. 2.3 illustrates the Gaussian noise with mean (variance) as 1.5 (10) over a base image with a constant pixel value of 100.

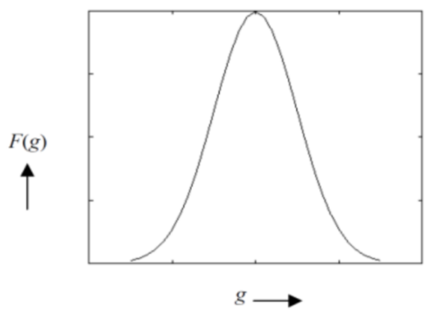

Figure 0.1: PDF for Gaussian Noise

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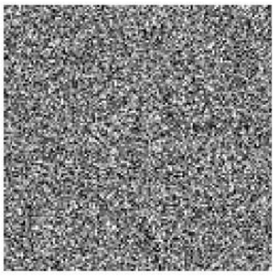

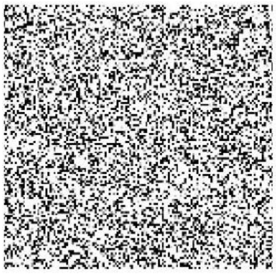

Figure 0.2: Gaussian Noise (mean=0 variance=0.05) **Figure 0.3: Gaussian Noise (mean=1.5 variance=10)**

2.2 Salt and Pepper Noise

Salt and pepper noise [3] is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values, a and b.

The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Unaffected pixels remain unchanged. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process. The probability density function for this type of noise is shown in Fig. 2.4. Salt and pepper noise with a variance of 0.05 is shown in Fig. 2.5.

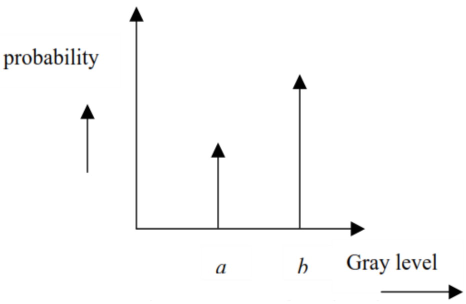

Figure 0.4: PDF for Salt and Pepper noise

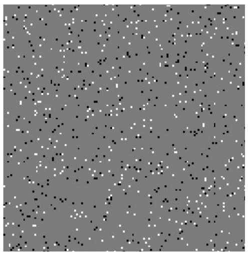

Figure 0.5: Salt and Pepper noise

2.3 Speckle Noise

Speckle noise is a multiplicative noise. This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR (Synthetic Aperture Radar) imagery. The source of this noise is attributed to random interference between the coherent returns. Fully developed speckle noise has the characteristic of multiplicative noise. Speckle noise follows a gamma distribution and is given as:

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!\,a^{\alpha}} e^{\frac{-g}{a}} \tag{0.4}$$

Where variance is $a^2\alpha$ and g is the gray level. On an image, speckle noise (with variance 0.05) looks as shown in Fig. 2.7. The gamma distribution is given below in Fig. 2.6.

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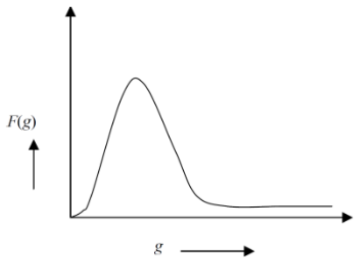

Figure 0.6: Gamma Distribution

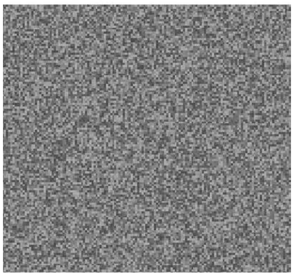

Figure 0.7: Speckle Noise

2.4 Brownian Noise

Brownian noise [4] comes under the category of fractal or $1/f$ noises. The mathematical model for $1/f$ noise is fractional Brownian motion. Fractal Brownian motion is a non-stationary stochastic process that follows a normal distribution. Brownian noise is a special case of $1/f$ noise. It is obtained by integrating white noise. It can be graphically represented as shown in Fig. 2.8. On an image, Brownian noise would look like Fig. 2.9.

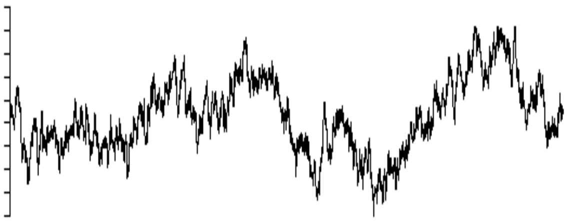

Figure 0.8: Brownian noise distribution

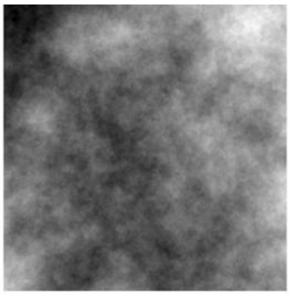

Figure 0.9: Brownian Noise

III. IMAGE DE-NOISING METHODS

Image de-noising is a very old problem for the researchers in the field of digital image processing. There are numerous techniques for image de-noising and all cannot be enlisted here. Therefore we will focus our discussion on the chosen few de-noising techniques namely Filtering technique, wavelet based technique and multifractal technique.

3.1 Spatial Filtering Techniques

Filtering in digital image processing is a basis function that is used to achieve many tasks such as noise reduction, interpolation and re-sampling. Filtering techniques is a standard process used in almost all types of image processing systems. Filters can be of different categories:

3.1.1 Linear Filters and Non-Linear Filters.

Linear filters are used to remove certain type of noise. Mainly we have two types of linear filters: 1. Mean or Averaging Filter and 2. Wiener filters. We will focus our discussion here, on averaging filter which are a good choice for removing impulse noise. One of the drawbacks of using the Linear filters is that they tend to blur the sharp edges and other fine details of image.

3.1.1.1 Mean or averaging filter:

This is a simple spatial filter that uses a sliding window filter. It replaces the center value in the window with the average / mean value of all the neighborhood pixels in the kernel or window. The window is usually square but it can be of any shape.

Advantage of Mean filter

1. Easy to implement
2. Used to remove the impulse noise or salt and pepper noise.

Disadvantages

1. It does not preserve the details of image. Some details are removed while using a mean filter.

Non Linear filters can be used to remove the noise without explicitly identifying it. This employs a low pass filtering on a group of pixels. In the past years a number of non linear filters have been developed like weighted median, conditioned rank selection and relaxed median to overcome the drawbacks of linear filters.

3.1.1.2 Median Filter

This is a best order static, non linear filter, whose response is based on the ranking of pixel values contained in the filter region. It is an easy to implement method of smoothing images. Median filter is used for reducing the amount of intensity variation between one pixel and the other pixel. In this filter we replace the pixel value of the image with the median value of all the neighboring pixel values. The median is calculated by sorting all the pixel values in the ascending order and then replace the middle pixel with the middle pixel value. The median filter gives the best result when the impulse noise percentage is below 0.1 %.

Advantages

1. It is easy to implement.
2. Can be used for de-noising different types of noises.

Disadvantages

1. Median filter tends to remove image details while reducing noise such as thin lines and corners.
2. Median filters do not give a satisfactory performance in case of signal dependent noise. To remove these difficulties different variations of median filters have been developed for better results.

3.2 Wavelet Transform Based Technique [6]

Unlike the traditional filtering technique, researchers are showing interest towards non-linear methods of de-noising manly based on thresholding the Discrete Wavelet Transform (DWT) coefficients which have been affected by additive white Gaussian noise. De-noising algorithms that use DWT consists of three steps.

1. Discrete wavelet transform is used to decompose the noisy image to obtain the wavelet coefficients.
2. These wavelet coefficients are de-noised with wavelet threshold.
3. Inverse transform is applied to the modified coefficients and get de-noised image.

The second step, known as thresholding, is a nonlinear technique, which operates on one wavelet coefficient at a time. In its basic form, each coefficient is thresholded by comparing threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept as it is or it is modified. Replacing the small noisy coefficient by zero and inverse wavelet transform on the resulted coefficient may lead to reconstruction with the essential signal characteristics and with less noise.

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During the last decade, a lot of new methods based on wavelet transforms have emerged for removing Gaussian random noise from images. The de-noising process is known as wavelet shrinkage or thresholding. Both VisuShrink and SureShrink are the best known methods of wavelet shrinkage proposed by Donoho and Johnstone. For VisuShrink, the wavelet coefficients w of the noisy signal are obtained first. Then with the universal threshold T (is the noise level and N is the length of the noisy signal), the coefficients are shrinked according to the soft shrinkage rule is used to estimate the noiseless coefficients. Finally, the estimated noiseless signal is reconstructed from the estimated coefficients. VisuShrink is very simple, but its disadvantage is to yield overly smoothed images because the universal threshold T is too large.

Just like VisuShrink, SureShrink also applies the soft shrinkage rule, but it uses independently chosen thresholds for each subband through the minimization of the Stein's unbiased risk estimate (SURE) (Stein, 1981). VisuShrink performs better than SureShrink, producing more detailed images.

3.2.1 VisuShrink

VisuShrink [6] is proposed by Donoho and Johnstone. This is also called as Universal threshold. VisuShrink is threshold by applying the Universal threshold. This threshold is given by:

$$t = \sigma\sqrt{2 \log n} \tag{0.1}$$

Where σ is the noise variance and n is the number of pixels in the image. It follows the hard thresholding rule. An estimate of the noise level σ is defined based on the median absolute deviation given by:

$$\sigma = \frac{median(\{|g_{j-1,k}|: k = 0,1, \dots 2^{j-1} - 1\})}{0.6745} \tag{0.2}$$

Where $g_{j-1,k}$corresponds to the detailed coefficient in the wavelet ransform. This asymptotically yields a mean square error (MSE) estimate as n tends to infinity. As n increases, we get bigger and bigger threshold, which tends to over smoothen the image.

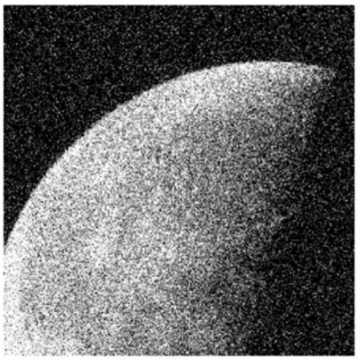

Figure 0.1: Image corrupted with Gaussian noise, variance 0.05.

Figure 0.2: Image after application of VisuShrink.

VisuShrink is known to yield recovered images that are overly smoothed. This is because VisuShrink removes too many coefficients. Another disadvantage is that it cannot remove speckle noise. It can only deal with an additive noise. VisuShrink follows the global thresholding [1] scheme where there is a single value of threshold applied globally to all the wavelet coefficients.

3.2.2 SureShrink

The SureShrink [6] threshold is developed by Donoho and Johnstone. It is a combination of Universal threshold and SURE threshold. THE goal of SureShrink is to minimize the MSE, defined as:

$$MSE = \frac{1}{n^2} \sum_{x,y=1}^{n} (z(x,y) - s(x,y))^2, \quad (0.3)$$

Where Z(x,y) is the estimate of the signal, s(x,y) is the original signal without noise and n is the size of the signal. The SureShrink threshold t^* is defined as:

$$t^* = min\left(t, \sigma\sqrt{2\log n}\right), \quad (0.4)$$

Where t denotes the value that minimizes Stein's Unbiased Risk Estimator, σ is the noise variance computed from Equation and n is the size of the image. In SureShrink, to the find threshold in every subband, i.e., called Subband adaptive thresholding. It is smoothness adaptive, that means unknown function contains abrupt changes or boundaries in the image, the reconstructed image also do.

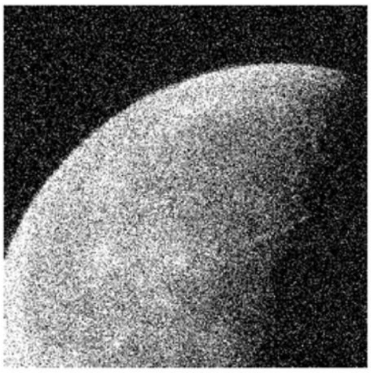

Figure 0.3: Input corrupted with Gaussian noise.

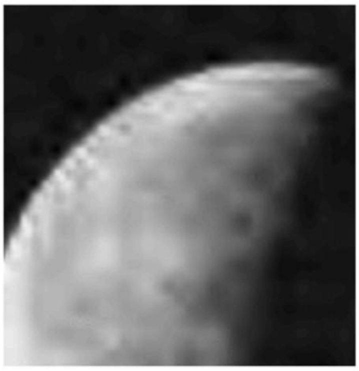

Figure 0.4: Image after SureShrink thresholding.

3.3 Multifractal Analysis Technique

The phenomenon of multifractals was first described by B. B. Mandelbrot in the context of fully developed turbulence [7]. Multifractal structures are generated by the multiplicative cascade of random processes, while additive processes generally produce simple fractals or monofractals. Functions that are everywhere continuous but nowhere differentiable are called fractals. They are objects of a complex structure, which exhibit the scaling property, that is, they exhibit the same properties at different scales. A fractal describes the local singularity and is usually measured using the Hurst parameter. The fractal dimension is the basic notion for describing structures that have scaling symmetry and is closely related to Hölder regularity. Fractal dimension is a non-integer value. Multifractal analysis gives a compact representation of the spectral decomposition of a signal into parts of equal strength of regularity [8]. This property makes multifractals very useful in image de-noising. Other applications of multifractals are in the fields of turbulence, rainfall, dynamical systems and in earthquake modeling [9].

Denoising by multifractal analysis is based on the fact that signal enhancement is equivalent to increasing the Hölder regularity at each point [10]. It is well adapted to the case where the signal to be recovered is very irregular and nowhere differentiable, a property relevant to fractal or self-similar structures. The local regularity of a function is measured by the local Hölder exponent, which is a local notion. Since the Hölder exponent is a local notion, this scheme is valid for signals that have sudden changes in regularity like discontinuities. To any continuous function we can associate its Hölder function, which gives the value of the Hölder exponent of the function at every point. In image de-noising using multifractal analysis, the Hölder regularity of the input signal is manipulated so that it is close to the regularity of the desired signal. The regularity of a function can be determined by geometrical and analytical ways. In the geometrical case, the regularity is obtained by computing the fractional dimensions of its graph. The analytical way considers a family of nested functional spaces and determines the ones to which the function actually belongs [10]. Generally, the second method is more practical and, hence, popular.

Denoising by multifractal analysis makes no assumptions on the type of noise present in the signal. Also, noise is considered to be independent of the signal. This procedure is suitable for signals, that are everywhere irregular, and the regularity of the original signal may vary rapidly in time or space.

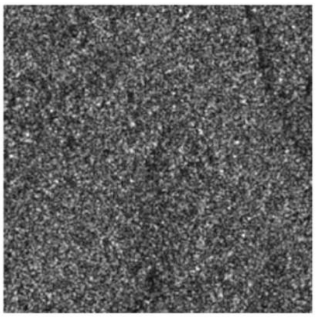

Figure 0.5: Input Image to multifractal pumpng.

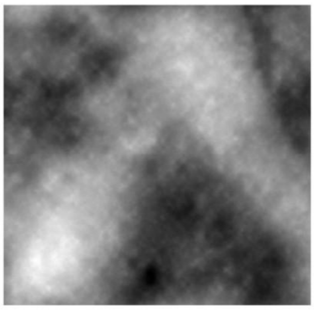

Figure 0.6: Image after multifractal pumping (spectrum shift value of 1.5)

It can be noticed from the input image (Fig. 3.5) that it is very irregular and no details are visible. This image is subjected to multifractal pumping. The resultant image is shown in Fig. 3.6. It can be observed from Fig. 3.6 that the inverted 'V' shaped river which cannot be seen in Fig. 3.5 can be seen in the output Fig. 3.6. This method is very helpful for the removal of noise from an image that has a complex and irregular nature. This method finds applications in denoising of Synthetic Aperture Radar (SAR) images.

IV. CONCLUSION

This chapter deals with the comparison of the denoising techniques, namely, linear and non-linear filtering, wavelet based denoising, and denoising by multifractal analysis. The signal to noise ratio of the output image is calculated which acts as a quantitative standard for comparison.

Table 0.1: SNR values for filtering approach.

Method	SNR of Input Image	SNR of Output Image	Noise type and Variance, σ
Mean Filter	18.88	27.43	Salt and Pepper, 0.05
Mean Filter	13.39	21.24	Gaussian, 0.05
Median Filter	18.88	47.97	Salt and Pepper, 0.05
Median Filter	13.39	22.79	Gaussian, 0.05

Table 0.2: SNR values for wavelet transform approach.

Method	SNR of Input Image	SNR of Output Image	Noise Type and Variance, σ
Visu Shrink	13.39	31.17	Gaussian, 0.05
Visu Shrink	18.88	19.01	Salt and Pepper, 0.05
Sure Shrink	13.39	36.46	Gaussian, 0.05
Sure Shrink	18.88	40.67	Salt and Pepper, 0.05

For the multifractal de-noising, the SNR computation is not compatible because, the brightness of the output image has been decreased. From the experimental and mathematical results it can be concluded that for salt and pepper noise, the median filter is optimal compared to mean filter. It produces the maximum SNR for the output image compared to the linear filters considered. In the case where an image is corrupted with Gaussian noise, the wavelet shrinkage de-noising has proved to be nearly optimal. SureShrink produces the best SNR compared to VisuShrink. De-noising salt and pepper noise using VisuShrink has proved to be inefficient. When the noise characteristics of the image are unknown, de-noising by multifractal 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.

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