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Study of Image De-noising Techniques for Facilitating the Process Selection to Determine the Best Suitable Approach for any given image Type

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***Abstract:* As the use of computers and automated systems is increasing in various fields so is the digitization of data. More and more data is being converted to digital format so as to make its availability easy. One of the major data formats that have been benefited by digitization are image and video format. Though digitization has made capturing, storing, managing, editing and transferring of images very convenient, but the process of capturing, storing and transferring many times introduces noise in images such as salt and paper noise, gaussian noise and speckle noise. This noise corrupts the image and thereby degrading the quality. There are many techniques that exist for removing or reducing the noise introduced in the image and these techniques are called denoising techniques. In this paper various denoising techniques are discussed, implemented and compared so as to identify and select the best approach for denoising depending on the working area and noise type.**

Keywords: **Denoising, Noise, SNR, Wavelet.**

I. INTRODUCTION

Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. Noise is the result of errors in image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. There are several ways that noise can be introduced into an image depending on how the image is created. For example if the image is scanned from a photograph film, the film grain is a source of noise. If the image is acquired directly in digital format, the mechanism for gathering the data can introduce noise. Electronic transmission of image data can also introduce noise.

The received image needs processing before it can be utilized as an input for decision making. Image denoising involves the manipulation of the image data to produce a visually high quality image. This thesis reviews the existing denoising algorithms, such as filtering approach, wavelet based approachetc. Concept of matched wavelets has been proposed for denoising of images and a comparison has been carried out with respect to available denoising algorithms in terms of SNR. Different noise models including additive and multiplicative types are used e.g gaussian noise, salt and pepper noise, speckle noise and Poisson noise. Selection of the denoising algorithm is application dependent therefore, it is necessary to have knowledge about the noise present in the image so as to select the appropriate denoising algorithm. The filtering approach has been proved to be the best when the image is corrupted with salt and pepper noise. The wavelet based approach finds applications in denoising images corrupted with Gaussian noise. A quantitative measure of comparison is provided by the signal to noise ratio of the image.

This paper is divided into five sections, section 1 consists of introduction, in section 2 various types of noise are discussed in brief, section 3 consists of various approaches of denoising, section 4 compares these algorithms along with results and section 5 consists of conclusion.

II. TYPES OF NOISE

Noise is undesired information that contaminates the image. In the image denoising process, information about the type of noise present in the original image plays a significant role. Typical images are corrupted with noise modeled 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

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

While the multiplicative noise satisfies

$$w(x, y)= s(x, y) \, x \, n(x, y) ,$$

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. 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. 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

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pixel.

A. Gaussian Noise

Gaussian noise is evenly distributed over the signal. 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

$$p(z) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(z-\mu)^2}{2\sigma^2}} \quad (2.1)$$

Where z represents the gray level, μ is the mean value, and σ2 is the variance of the noise.

B. Salt and Pepper Noise

(a) Salt and pepper noise 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.

$$p(z) = \begin{cases} P_a & \text{if } z = a \\ P_b & \text{if } z = b \\ 0 & \text{otherwise} \end{cases} \quad (2.2)$$

(b)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.

C. 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

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!a^{\alpha}} e^{-\frac{g}{a}} \quad (2.3)$$

Where variance is $a^2\alpha$ and g is the gray level.

III. APPROACHES OF DENOISING

Traditional denoising techniques have been the filtering method which can be categorized into two types i.e, Linear and Non linear approach. Linear filtering using Mean filter and Least Mean Square (LMS) adaptive filter and nonlinear filtering based on median filter are discussed in this section.

A. Linear Approaches

1 Mean Filter

A Mean filter acts on an image by smoothing it i.e. it reduces the intensity variation between adjacent pixels. The mean filter is nothing but a simple sliding window spatial filter that replaces the center value in the window with the average of all the neighboring pixel values including it. By doing this, it replaces pixels that are unrepresentative of their surroundings. It is implemented with a convolution mask, which provides a result that is a weighted sum of the values of a pixel and its neighbors. It is also called a linear filter. The mask or kernel is a square. Often a 3x3 square kernel is used. If the coefficients of the mask sum up to one, then the average brightness of the image is not changed. If the coefficients sum to zero, the average brightness is lost, and it returns a dark image. The mean or average filter works on the shift-multiply-sum principle.

2 Adaptive Filter

An adaptive filter[9] does a better job of denoising images compared to the averaging filter. The fundamental difference between the mean filter and the adaptive filter lies in the fact that the weight matrix varies after each iteration in the adaptive filter while it remains constant throughout the iterations in the mean filter. Adaptive filters are capable of denoising non-stationary images, i.e. images that have abrupt changes in intensity. Such filters are known for their ability in automatically tracking an unknown circumstance or when a signal is variable with little a priori knowledge about the signal to be processed. In general, an adaptive filter iteratively adjusts its parameters during scanning the image to match the image generating mechanism. This mechanism is more significant in practical images, which tend to be non-stationary.

B. Non Linear Approaches- Median Filter

A Median filter belongs to the class of nonlinear filters unlike the mean filter. The median filter also follows the moving window principle similar to the mean filter. A 3x 3, 5x5, or 7x7 kernel of pixels is scanned over pixel matrix of the entire image. The median of the pixel values in the window is computed and the center pixel of the window is replaced with the computed median. Median filtering is done by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value.

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C. Wavelet Based Image Denoising Technique

Wavelet transform performs a high degree of decorrelation between neighboring pixels and it provides a distinct localization of the image in the spatial as well as the frequency domain. This transform also provides an elegant sub-band framework in which both high and low frequency components of the image can be analyzed separately. Recently, various wavelet-based methods have been proposed for the purpose of image enhancement and restoration. Basic wavelet image restoration methods are based on thresholding in the sense that each wavelet coefficient of the image is compared to a given threshold. If the coefficient is smaller than the threshold, then it is set to zero, otherwise it is kept or slightly reduced in magnitude. The intuition behind such an approach follows from the fact that the wavelet transform is efficient at energy compaction, thus small wavelet coefficients are more likely due to noise, and large coefficients are generally due to important image features, such as edges. Most of the efforts in the literature have concentrated on developing threshold selection criteria. Originally, Donoho and Johnstone [11] proposed the use of a universal threshold uniformly throughout the entire wavelet decomposition tree. Then the use of different thresholds for different sub band and levels of the wavelet tree was found to be more efficient. Some methods of selecting thresholds that are adaptive to different spatial characteristics have been proposed and investigated [12]. It was found that such adaptivity in the threshold selection tends to improve the wavelet thresholding performance because it accounts for additional local statistics of the image, such as smooth or edge regions. These observations are consistent with the nature of adaptive processes which account for the local statistics and characteristics of the image. In general, adaptive approaches have been found to be more effective than their global counterparts.

(b) As has been evident from the discussion so far, wavelets have tremendous potential for image processing. Wavelet based techniques are fast emerging as the preferred technique for image de-noising and compression.

(c) Till date several wavelet based noise reduction techniques have been reported [2][6]. Amongst these, the non-linear thresholding schemes are the simplest, yet very effective. Next, some of these wavelet based denoising schemes are discussed.

1. General Thresholding Based Denoising Procedure

Any wavelet based image processing operation involves computing the wavelet transform, modifying the wavelet coefficients and reconstructing by computing the inverse wavelet transform of the modified coefficients.

One of the earlier wavelet based denoising methods called Wavelet Shrinkage involved all the wavelet coefficients being shrunk by some factor decided by Bayesian estimation procedure or by the probability of a given coefficient being clean [11]. A simpler and more effective method was to decide if a coefficient is likely to be 'clean' or 'noisy' depending on whether its absolute magnitude crosses a certain threshold or not. This is a non-linear operation.

General procedure for denoising the image by thresholding is summarized below:

1. Select a wavelet and the number of scales **P**. Then compute the discrete wavelet transform (DWT) of the image. The choice of wavelet depends upon the application. For image denoising, the Daubechies wavelets, of which the Haar wavelet is a special case, are extremely popular. Number of scales depends on the amount of noise reduction required and on the computational speed.
2. The wavelet detail coefficients of one or more scales are modified according to the threshold value. The approximation is not modified. The manner in which the coefficients are modified will be explained in the next section.
3. Inverse wavelet transform of the modified coefficients is computed to obtain the denoised image. depend on the level of accuracy of the estimation method.

2. Hard and Soft Thresholding

Considering the manner in which the detail coefficients are modified, the thresholding process can be classified as either hard or soft thresholding.

1. In hard thresholding, those coefficients whose absolute values are below the threshold are set to zero. Mathematically, the modified coefficient value is given by

$$w_j^c(m,n) = T_{hard}\left(w_j^c(m,n),\lambda\right) \quad (3.1)$$

This is the same as;

$$w_j^c(m,n) = w_j^c(m,n)\,u\left(\left|w_j^c(m,n)\right| - \lambda\right) \quad (3.2)$$

Where $w_j^c(m,n)$ is the j^{th} scale coefficients of the coordinates (m,n) of the component c= H,V,D and λ is the threshold value. An inherent problem in hard thresholding is that there is a discontinuity at the threshold value.

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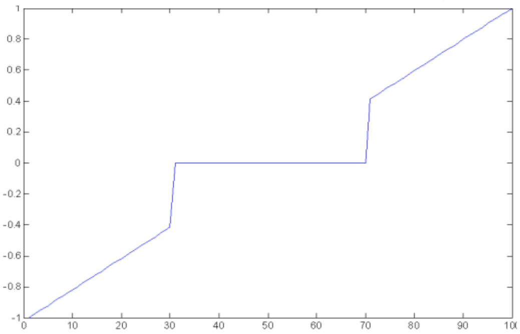

Fig 1: Hard Thresholding

2. Soft thresholding involves first performing a hard thresholding and then scaling the non-zero coefficients towards zero. By doing this, the discontinuity at the threshold value is eliminated.

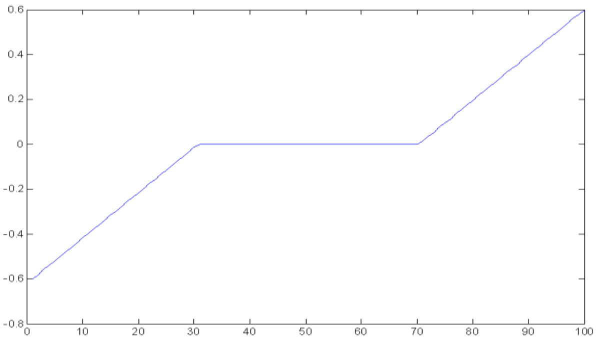

Fig 2: Soft Thresholding

Mathematically, the modified coefficient value is given by;

$$w_j^c(m,n) = T_{soft}\left(w_j^c(m,n),\lambda\right) \quad (3.3)$$

$$w_j^c(m,n) = sgn\left(w_j^c(m,n)\right)\frac{\left(w_j^c(m,n)-\lambda+\left|\left|w_j^c(m,n)\right|-\lambda\right|\right)}{2} \quad (3.4)$$

Thresholds can also be classified as non-adaptive or adaptive to scale and possibly sub-band, depending on whether the threshold value is different for different scales and components. It is clear that since noise affects different scales and sub-bands components differently, the same threshold will not work for every scale and sub-band component.

3 Universal Threshold

This threshold, proposed by Donoho [11] is a non-adaptive one in which the same threshold value is applied to all components and scales. The threshold value is given as $\tau = \sigma\sqrt{2\log N}$ where σ is the standard deviation of the additive white Gaussian noise contamination, and N is the total number of pixels. This results in over-smoothing of images.

4 Bayes-Shrink Threshold

Bayes-Shrink was proposed by Chang, Yu and Vetterli. The aim of this method is to minimize the Bayesian risk, and hence its name, Bayes-Shrink. It uses soft thresholding and is sub band-dependent, which means that thresholding is done at each band of resolution in the wavelet decomposition. Denoting the variance of the noise in the image as σ^2 and σ_{w_j} being the standard deviation of the coefficients of a particular sub-band at j^{th} scale, the threshold is given by $\tau = \frac{\sigma^2}{\sigma_{w_j}}$.

5 Pan Threshold

Pan et al., proposed this as a hard threshold [6] with a non orthogonal wavelet expansion. The threshold value is given by $\tau = c\sigma j$, where σj is the standard deviation of noise at the j^{th} scale and ‘c’ is a constant. The value of c is taken to be around 3, since the values of Gaussian distributed noise are in high probability within three times its standard deviation.

6 Adaptive Noise Cancelling

Since noise affects differently at different instants, a need was felt to evolve a method that adaptively removes the noise, based on the noise information present in the observed signal. The concept of adaptive noise cancellation was proposed by Bernard Widrow et al in 1975[9]

7 Image Denoising by Block Matching and Filtering

Intuitively sliding-window transform processing along with block matching can be effectively employed for denoising of images. The present approach is an extension of the work done by Dabov et.al [13]. For a single noisy image, as we process image blocks in a sliding manner, we search for blocks that exhibit similarity to the currently processed one. The matched blocks are stacked together to form a 3D array. In this manner high correlation can be induced along the dimension of the array in which the blocks are stacked. This correlation can be exploited by applying a 3D de-correlating unitary transform which produces a sparse representation of the true signal in 3D transform domain. Efficient noise attenuation can be done by applying hard-thresholding or Wiener filtering on the transform coefficients. This result in improved denoising performance and effective detail preservation in the local estimates of the matched blocks, which are reconstructed by an inverse 3D transform of the filtered coefficients.

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IV. COMPARISON OF DENOISING TECHNIQUES

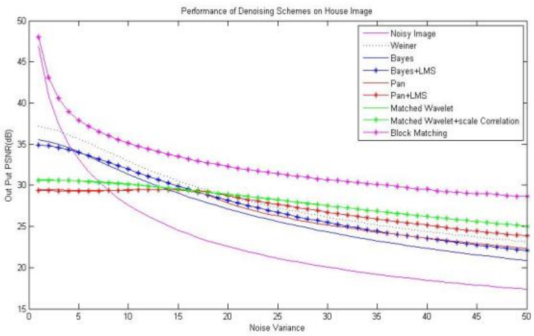

Fig 3: Comparison of Denoising Techniques (Gaussian Noise)

Following is evident from the results:-

Gaussian Noise Weiner Filters, although being the optimum filters for removing Gaussian Noise from the images, however it is possible to further improve the process of denoising using LMS filter. Multiscale product based denoising provides the best SNR improvement over the complete noise range. Response of block matching and filtering based denoising was better at lower noise variance value whereas it falls below other denoising techniques at higher noise variance values.

Speckle Noise Multiscale product based denoising response improved over the moderate value of noise however it was below Wiener based denoising response at other part of noise spectrum. Block matching based denoising gave good improvement with respect to SNR over the complete noise range.

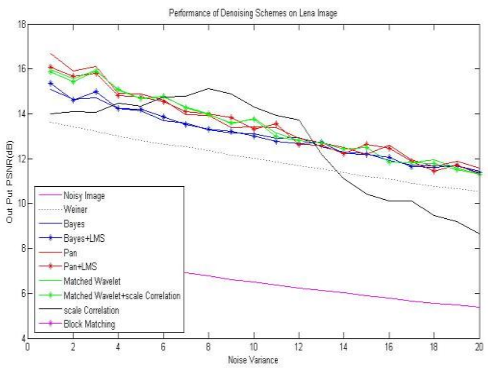

Fig 4: Comparison of Denoising Techniques (Speckle Noise)

Block matching and matched wavelet based denoising can be exploited for denoising of satellite images like SAR images.

Salt and Pepper Noise Block matching and filtering based denoising performed well during low value of noise only. Multiscale product based denoising response was poor.

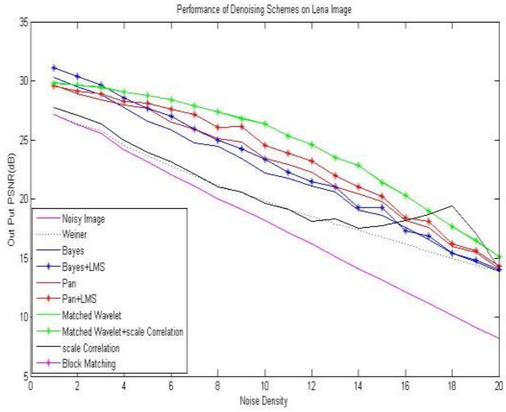

Fig 5: Comparison of Denoising Techniques (Salt and Pepper Noise)

Existing Wavelet based denoising schemes like the Bayes Thresholding and Pan Thresholding can be significantly improved by employing LMS algorithm. In any denoising scheme, noise estimation is of paramount importance and the performance of denoising technique depends to a large extent on noise estimation. The adaptation of Matched Wavelets provided us with promising results that were better than the wiener filter for all type of noises under consideration i.e Gaussian, Speckle and Salt and pepper noise. Median filter still outperformed matched wavelets in case of Salt and Pepper noise removal. Different denoising techniques perform differently for different types of images. This can be attributed to the different statistical features of each image.

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