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Image Denoising Techniques-An Overview

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Abstract: *A fundamental step in image processing is the step of removing various kinds of noise from the image. Sources of noise in an image mostly occur during storage, transmission and acquisition of the image .Image denoising is a applicable issue found in diverse image processing and computer vision problems. There are various existing methods to denoise image. The important property of a good image denoising model is that it should completely remove noise as far as possible as well as preserve edges. The image denosing technique will be mainly depending on the type of the image and noise in cooperating with it. There have been several published algorithms and each approach has its assumptions, advantages, and limitations. This paper presents a review of some noise models and significant work in the area of image denoising.*
Keywords: *Image Denoising, Filters, Transform Domain, Wavelet Thresholding*

I. Introduction

An image is often corrupted by noise in its acquisition and transmission. Image denoising is used to remove the additive noise while retaining as much as possible the important signal features. Generally, data sets collected by image sensors are contaminated by noise. Imperfect instruments, problems with data acquisition process, and interfering natural phenomena can all corrupt the data of interest. Thus noise reduction is an important technology in Image Analysis and the first step to be taken before images are analyzed. Therefore, Image Denoising techniques are necessary to prevent this type of corruption from digital images[1] . .

Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise is observed in ultrasound images whereas Rician noise affects MRI images. Different noise sources like dark current noise introduced different types of noises[4]. Dark current noise usually present due to the thermally generated electrons at sensor sites. It is proportional to the exposure time and highly dependent on the sensor temperature. Shot noise which follows a Poisson distribution, is due to the quantum uncertainty in photoelectron generation. Amplifier noise and quantization noise arises when number of electrons converts into pixel intensities Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption.

Spatial filters like mean and median filter are used to remove the noise from image. But the disadvantage of spatial filters is that these filters not only smooth the data to reduce noise but also blur edges in image. Therefore, Wavelet Transform is used to preserve the edges of image[11]. It is a powerful tool of signal or image processing for its multi-resolution possibilities. Wavelets give a superior performance in image denoising due to properties such as sparsity and multiresolution structure. With Wavelet Transform gaining popularity in the last two decades various algorithms for denoising in wavelet domain were introduced. The focus was shifted from the Spatial and Fourier domain to the Wavelet transform domain[14]. This paper provides different methodologies for noise reduction. It also gives us the insights into the methods to conclude which method will provide the consistent and approximate estimate of original image from given its degraded version.

The paper is organized as follows; Section 2 introduces the concept of different noise models. Section 3 provides the types of noise that in cooperate with the images. Section 4 explains the type of denoising methodologies, the implementation and the methodology where discussed in the section 5 finally the concluding remarks is given in section 6.

II. Noise Models

Noise is present in image either in additive or multiplicative form.

2.1 Additive Noise Model

Noise signal that is additive in nature gets added to the original signal to generate a corrupted noisy signal and follows the following rule:

$w(x, y) = s(x,y) + n(x,y)$ ....(1)

where, s(x, y) is the original image intensity and n(x,y) denotes the noise introduced to produce the corrupted signal w(x,y) at (x,y) pixel location .

2.2 Multiplicative Noise Model
In this model, noise signal gets multiplied to the original signal. The multiplicative noise model follows the following rule:

$w(x, y) = s(x, y) \times n(x,y)$ ....(2)

III. Types Of Noise

Various types of noise have their own characteristics and are inherent in images in different ways.

3.1 Amplifier Noise

The typical model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity. In color cameras, blue color channels are more amplified than red or green channel, therefore, more noise can be present in the blue channel. Amplifier noise is a major part of the "read noise" of an image sensor, that is, of the consistent noise level in dark areas of the image . This type of noise has a Gaussian distribution, which has a bell shaped probability distribution function. Graphically it is represented as,

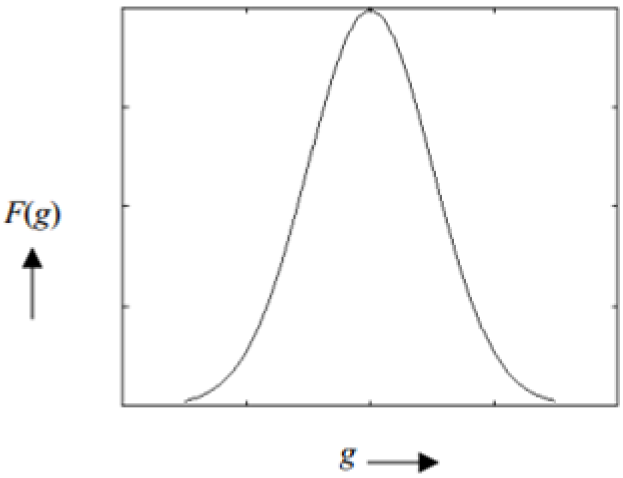

Figure1. Gaussian Distribution

3.2 Impulsive Noise

Impulsive noise is sometimes called as salt-and- pepper noise or spike noise. This kind of noise is usually seen on images. It represents itself as arbitrarily occurring white and black pixels. An image that contains impulsive noise will have dark pixels in bright regions and bright pixels in dark regions. It can be caused by dead pixels, analog-to-digital converter errors and transmitted bit errors.

3.2.1 Detection of Impulsive Noise

The noise affecting the image is stated to be an impulsive noise, if the ratio of the mean of the dynamics of the grey levels of the homogeneous regions to the maximum value of the dynamics of the grey levels of the homogeneous regions is greater than a threshold value then .

$(\text{mean}(D(n))/\max(D(n)))>\lambda$ ……….. (4)

3.3 Speckle Noise

Speckle noise is considered as multiplicative noise. It is a granular noise that degrades the quality of images obtained by active image devices such as active radar and synthetic aperture radar (SAR) images. Due to random fluctuations in the return signal from an object in conventional radar that is not big as single image-processing element, speckle noise occurs. It increases the mean grey level of a local area. Speckle noise makes image interpretation difficult in SAR images caused mainly due to coherent processing of backscattered signals from multiple distributed targets.

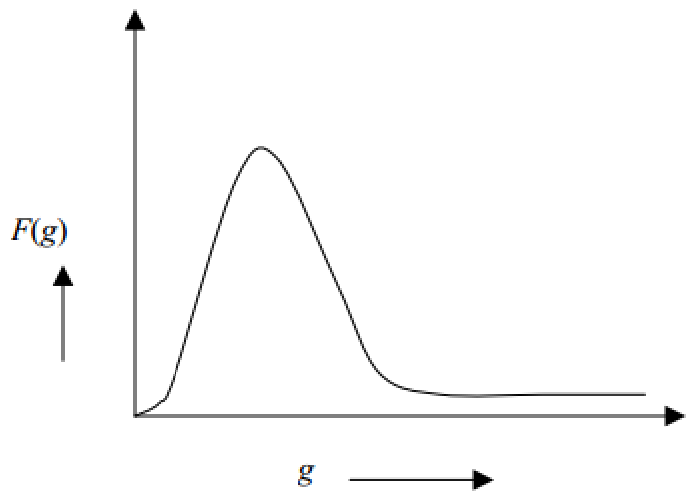

Figure2. Gamma Distribution

IV. Classification Of Denoising Methodology

There are three basic approaches to image denoising – Spatial Filtering, Transform Domain Filtering and Wavelet Thresholding Method. Objectives of any filtering approach are:

- To suppress the noise effectively in uniform regions.
- To preserve edges and other similar image characteristics.
- To providea visually natural appearance.

4.1 Spatial Filtering

A traditional way to remove noise from image data is to employ spatial filters. spatial filtering is the method of choice in situations when only additive noise is present. It can be further classified into 2 categories: Linear filters and Non Linear Filters

4.1.1 Linear Filters

It is the method of choice in situations when only additive noise is present. A mean filter is the optimal linear for Gaussian noise in the sense of mean square error. It blurs sharp edges, destroy lines and other fine details of image. It includes Mean filter and Wiener filter**.** 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 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. Wiener method implements spatial smoothing and its model complexity control correspond to choosing the window size. To overcome the weakness of the Wiener filtering, Donoho and Johnstone proposed the wavelet based denoising scheme

4.1.1.1 Mean filter

This filter provides smoothness in an image by reducing the intensity variations between the adjacent pixels. Mean filter is essentially an averaging filter. It applies mask over each pixel in the signal. Therefore, to make a single pixel, each of components of pixel which falls under mask are average filter. The main disadvantage is that edge preserving criteria is poor in Mean filter.

4.1.1.2 Wiener Filter

It is a filter that takes statistically approach to filter out noise that has corrupted a signal. Desired frequency response can be acquired using this filter. The Wiener filter approaches filtering from a different angle. For performing filtering operation it is essential to have knowledge of the spectral properties of the original signal and the noise, in achieving the criteria one can get the LTI filter whose output will be as close as original signal as possibl**e**.

4.1.2 Non Linear Filters

It is the method of choice in situations when multiplicative and function based noise is present. 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 pictures invisible. In recent years, a variety of nonlinear median type filters such as weighted median, rank conditioned rank selection , and relaxed median have been developed to overcome this drawback. With non-linear filters, the noise can be removed without identifying it exclusively. In this case, the median of the neighborhood pixels determine the value of an output pixel. Spatial filters make use of a low pass filtering on groups of pixels with the statement that the noise occupies the higher region of frequency spectrum. Normally, spatial filters eliminate noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible.

4.1.2.1 Median Filter

Median filter belongs to the class of non linear filter. Median filtering is done by, firstly finding the median value by across the window, and then replacing each entry in the window with the pixel's median value. If the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. But, for an even number of entries, there is more than one possible median. It is a robust filter. Median filters used for providing smoothness in image processing and time series processing . The advantage of using median filtering is that it is much less sensitive than the mean to extreme values (called outliers). Therefore, it is able to remove these outliers without reducing the sharpness of image.

4.2 Transform Domain Filtering

The transform domain filtering can be divided according to choice of basic functions. They mainly classified in to the non- data adaptive transform and data adaptive transform

4.2.1 Non- Data Adaptive Transform

a. Spatial Frequency Filtering

It refers the use of low pass filters using fast Fourier Transform. The noise is removed by deciding a cut-off frequency and adapting a frequency domain filter when the components of noise are decorrelated from useful signal . The main disadvantage of Fast Fourier Transform (FFT) is the fact that the edge information is spread across frequencies because of FFT basis function and it is not being localized in time or space which means that time information is lost and hence low pass filtering results in smearing of the edges. But the localized nature of Wavelet Transform both in time and space provides a particularly useful method for image denoising when the preservation of edges in the scene is of importance.

b. Wavelet Domain Filtering

Working in Wavelet domain is preferred because the Discrete Wavelet Transform (DWT) make the signal energy concentrate in a small number of coefficients, hence, the DWT of the noisy image consists of a small number of coefficients having high Signal to Noise Ratio (SNR) while relatively large number of coefficients is having low SNR. After removing the coefficients with low SNR (i.e., noisy coefficients) the image is reconstructed by using inverse DWT. As a result, noise is removed or filtered from the observations. A major advantage of Wavelet methods is that it provides time and frequency localization simultaneously. Moreover, wavelet methods characterize such signals much more efficiently than either the original domain or transforms with global basis elements such as the Fourier transform

b.1 Wavelet Based Thresholding

Wavelet Thresholding is a signal estimation technique that exploits the capabilities of Wavelet transform for signal denoising. It removes noise by killing coefficients that are irrelevant relative to some threshold that turns out to be simple and effective, depends heavily on the choice of a Thresholding parameter and the choice of this threshold determines, to a great extent the efficiency of denoising. There are several studies on Thresholding the Wavelet coefficients. The process, commonly called Wavelet Shrinkage,

b.1.1 Thresholding Method

There are various Thresholding techniques which are used for purpose of image denoising such as hard and soft Thresholding. Hard Thresholding which is based on keep and kill rule is more instinctively appealing and also it introduces artifacts in the recovered images whereas soft Thresholding is based on shrink and kill rule, as it shrinks the coefficients above the threshold in absolute value . In practice, soft Thresholding has been used over hard Thresholding because it gives more visually pleasant image as compared to hard Thresholding and reduces the abrupt sharp changes that occur in hard Thresholding. In MATLAB, by default, hard Thresholding is used for compression and soft Thresholding for denoising.

b.1.2 Threshold Selection Rules

In image denoising applications, the selection of threshold value should be such that Peak Signal to Noise Ratio (PSNR) is maximize . Finding an optimal value for Thresholding is not an easy task. A small threshold will pass all the noisy coefficients and hence the resultant images may still be noisy whereas a large threshold makes more number of coefficients to zero, which leads to smooth image and image processing may cause blur and artifacts, and hence the resultant images may lose some signal values . Threshold selection is based on non adaptive threshold and adaptive threshold.

b.1.2.1 Non Adaptive Threshold

Visu Shrink is non adaptive universal threshold, which depends only on a number of data points. It is found to yield an overly smoothed estimate .It suggests a best performance in terms of mean square error (MSE), when number of pixels reaches infinity. Its threshold value is quite large due to its dependency on number of pixels in image . The drawback is that it cannot remove the Speckle noise. It can only deal with additive noise.

b.1.2.2 .Adaptive Threshold

There are two types of adaptive threshold i.e. Sure Shrink and Bayes Shrink**.** Sure Shrink derived from minimizing Stein's Unbiased Risk Estimator, an estimate of MSE risk. It is a combination of universal threshold and SURE threshold. It is used for suppression of noise by Thresholding the empirical wavelet coefficient.. The goal of Sure Shrink is to minimize the mean square error**.** Sure shrink suppresses the noise by Thresholding the empirical wavelet coefficient . The Bayes Shrink method has been attracting attention recently as an algorithm for setting different thresholds for every sub band. Here sub bands are frequency bands that differ from each other in level and direction . The purpose of this method is to estimate a threshold value that minimizes the Bayesian risk assuming Generalized Gaussian Distribution (GGD) prior.

b.2. Non-orthogonal Wavelet Transforms

Undecimated Wavelet Transform (UDWT) has also been used for decomposing the signal to provide visually better solution. Since UDWT is shift invariant it avoids visual artifacts such as pseudo-Gibbs phenomenon. Though the improvement in results is much higher, use of UDWT adds a large overhead of computations thus making it less feasible. In normal hard/soft thresholding was extended to Shift Invariant Discrete Wavelet Transform. In Shift Invariant Wavelet Packet Decomposition (SIWPD) is exploited to obtain number of basis functions. Then using Minimum Description Length principle the Best Basis Function was found out which yielded smallest code length required for description of the given data. Then, thresholding was applied to denoise the data. In addition to UDWT, use of Multiwavlets is explored which further enhances the performance but further increases the computation complexity. The Multiwavelets are obtained by applying more than one mother function (scaling function) to given dataset. Multiwavelets possess properties such as short support, symmetry, and the most importantly higher order of vanishing moments. This combination of shift invariance & Multiwavelets is implemented in which give superior results for the Lena image in context of MSE.

b.3. Wavelet Coefficient Model

This approach focuses on exploiting the multiresolution properties of Wavelet Transform. This technique identifies close correlation of signal at different resolutions by observing the signal across multiple resolutions. This method produces excellent output but is computationally much more complex and expensive. The modeling of the wavelet coefficients can either be deterministic or statistical.

b.3.1 Deterministic

The Deterministic method of modeling involves creating tree structure of wavelet coefficients with every level in the tree representing each scale of transformation and nodes representing the wavelet coefficients. This approach is adopted in . The optimal tree approximation displays a hierarchical interpretation of wavelet decomposition. Wavelet coefficients of singularities have large wavelet coefficients that persist along the branches of tree. Thus if a wavelet coefficient has strong presence at particular node then in case of it being signal, its presence should be more pronounced at its parent nodes. If it is noisy coefficient, for instance spurious blip, then such consistent presence will be missing, tracked wavelet local maxima in scalespace, by using a tree structure. Other denoising method based on wavelet coefficient trees is proposed by Donoho

b.3.2 Statistical Modeling of Wavelet Coefficients

This approach focuses on some more interesting and appealing properties of the Wavelet Transform such as multiscale correlation between the wavelet coefficients, local correlation between neighborhood coefficients etc. This approach has an inherent goal of perfecting the exact modeling of image data with use of Wavelet Transform. The following two techniques exploit the statistical properties of the wavelet coefficients based on a probabilistic model.

b.3.2.1. Marginal Probabilistic Model

A number of researchers have developed homogeneous local probability models for images in the wavelet domain. Specifically, the marginal distributions of wavelet coefficients are highly kurtotic, and usually have a marked peak at zero and heavy tails. The Gaussian mixture model (GMM)and the generalized Gaussian distribution (GGD) are commonly used to model the wavelet coefficients

distribution. Although GGD is more accurate, GMM is simpler to use. the wavelet coefficients are assumed to be conditionally independent zero-mean Gaussian random variables, with variances modeled as identically distributed, highly correlated random variables. An approximate Maximum A Posteriori (MAP) Probability rule is used to estimate marginal prior distribution of wavelet coefficient variances. All these methods mentioned above require a noise estimate, which may be difficult to obtain in practical applications. Simoncelli and Adelson used a twoparameter generalized Laplacian distribution for the wavelet coefficients of the image, which is estimated from the noisy observations. proposed the use of adaptive wavelet thresholding for image denoising, by modeling the wavelet coefficients as a generalized Gaussian random variable, whose parameters are estimated locally

b.3.2.2. Joint Probabilistic Model

Hidden Markov Models (HMM) models are efficient in capturing inter-scale dependencies, whereas Random Markov Field models are more efficient to capture intrascale correlations. The complexity of local structures is not well described by Random Markov Gaussian densities whereas Hidden Markov Models can be used to capture higher order statistics. The correlation between coefficients at same scale but residing in a close neighborhood are modeled by Hidden Markov Chain Model where as the correlation between coefficients across the chain is modeled by Hidden Markov Trees. Once the correlation is captured by HMM, Expectation Maximization is used to estimate the required parameters and from those, denoised signal is estimated from noisy observation using wellknown MAP estimator. a model is described in which each neighborhood of wavelet coefficients is described as a Gaussian scale mixture (GSM) which is a product of a Gaussian random vector, and an independent hidden random scalar multiplier. Strela et al. described the joint densities of clusters of wavelet coefficients as a Gaussian scale mixture, and developed a maximum likelihood solution for estimating relevant wavelet coefficients from the noisy observations. Another approach that uses a Markov random field model for wavelet coefficients was proposed by Jansen and Bulthel. A disadvantage of HMT is the computational burden of the training stage. In order to overcome this computational problem, a simplified HMT, named as Uhmt, was proposed.

5.2.3 Data-Adaptive Transforms

Recently a new method called Independent Component Analysis (ICA) has gained wide spread attention. The ICA method was successfully implemented in denoising Non-Gaussian data. One exceptional merit of using ICA is it’s assumption of signal to be Non-Gaussian which helps to denoise images with Non-Gaussian as well as Gaussian distribution. Drawbacks of ICA based methods as compared to wavelet based methods are the computational cost because it uses a sliding window and it requires sample of noise free data or at least two image frames of the same scene. In some applications, it might be difficult to obtain the noise free training data.

V. Implementation Methodology

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption.

From the data flow diagram we can say that, when noise is add to the image such image called noisy image. Pre filter process is done by using image denosing technique which will be depending on the type of the image and the noise in cooperate with the image

VI. Conclusion

An image is often corrupted by noise during its acquisition and transmission. Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), minimum mean square error (MMSE) as well as in terms of visual quality of the images. Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), minimum mean square error (MMSE) as well as in terms of visual quality of the images. variance of the noise or the noise model. Thus, most of the image denoising algorithms consider known variance of the noise and the noise model to compare the performance with different image denoising algorithms. Gaussian Noise with different variance values is added in the natural images to test the performance of the image denoising algorithm.

The purpose of this paper is to present a survey of digital image denoising approaches. As images are very important in each and every field so, Image Denoising is an important pre-processing task before further processing of image like segmentation, feature extraction, texture analysis etc. The above survey shows the different type of noises that can corrupt the image and different type of filters which are used to improve the noisy image. The study of various denoising techniques for digital images shows that wavelet filters outperforms the other standard spatial domain filters. Filtering is done by Mean and Median Filter. And three different wavelet thresholding techniques have been discussed i.e. Universal Thresholding, Bayes Shrink and VisuShrink. The results conclude that Bayes shrinkage method has high PSNR at different noise variance and low MSE. Also the comparison of Wavelet thresholding methods at different decomposition level has been discussed

Spatial filters operate by smoothing over a fixed window and it produces artifacts around the object and sometimes causes over smoothing thus causing blurring of image. Therefore, Wavelet transform is best suited for performance because of its properties like sparsity, multiresolution and multiscale nature.

It is expected that the future research will focus on building robust statistical models of non-orthogonal wavelet coefficients based on their intra scale and inter scale correlations. Such models can be effectively used for image denoising and compression.

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