



Study of Image Denoising and Its Techniques

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Abstract— *Noise Suppression from images is one of the most important concerns in digital image processing. Impulsive noise is one such noise, which may corrupt images during their acquisition or transmission or storage etc. Removing noise from any processed image is very important noise should be removed in such a way that important information of image should be preserved. Removing noise from the original signal is still a challenging problem for researchers. Image noise is random variation of brightness or colour information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information. In medical image processing, image denoising has become a very essential exercise all through the diagnose. There have been several published algorithms and each approach has its assumptions, advantages, and limitations. This paper presents a review of some significant work in the area of image denoising.*

Keywords—*image noise, denoising, filters, transform domain, wavelet.*

I. INTRODUCTION

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 [1]. Digital images may be contaminated by different sources of noise. Noise may be generated due to imperfect instruments used in image processing, problems with the data acquisition process, and interference, all of which can degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression also. Different types of noises are introduced by different noise sources like dark current noise is 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 has the characteristics of Poisson distribution, is due to the quantum uncertainty in photoelectron generation. Amplifier noise and quantization noise occur during the conversion of number of electrons to pixel intensities [2].

II. EVALUATION OF RESEARCH

Image Denoising has remained a fundamental problem in the field of image processing. 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. Although Donoho's concept was not revolutionary, his methods did not require tracking or correlation of the wavelet maxima and minima across the different scales as proposed by Mallat [3]. Thus, there was a renewed interest in wavelet based denoising techniques since Donoho [4] demonstrated a simple approach to a difficult problem. Researchers published different ways to compute the parameters for the thresholding of wavelet coefficients. Data adaptive thresholds [5] were introduced to achieve optimum value of threshold. Later efforts found that substantial improvements in perceptual quality could be obtained by translation invariant methods based on thresholding of an Undecimated Wavelet Transform [6]. These thresholding techniques were applied to the nonorthogonal wavelet coefficients to reduce artifacts. Multiwavelets were also used to achieve similar results. Probabilistic models using the statistical properties of the wavelet coefficient seemed to outperform the thresholding techniques and gained ground. Recently, much effort has been devoted to Bayesian denoising in Wavelet domain. Hidden Markov Models and Gaussian Scale. Data adaptive transforms such as Independent Component Analysis (ICA) have been explored for sparse shrinkage. The trend continues to focus on using different statistical models to model the statistical properties of the wavelet coefficients and its neighbours [7].

III. IMAGE NOISE AND ITS TYPES

Image noise is random variation of brightness or color information in images, and is usually an aspect of electronic noise. Randomly-spaced speckles, called noise, can appear in digital images. When noise is present, image detail and clarity are reduced, sometimes significantly. Noise is most noticeable in even areas of color such as shadows. Noise in image: $w(x, y) = s(x, y) + n(x, y)$

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.

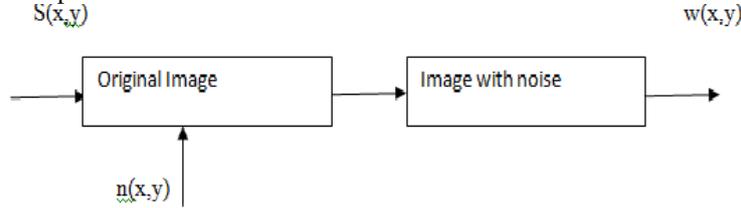


Figure:1 Noise Model

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 $z(x,y)$ as shown in figure

Different types of noises:

- Amplifier noise (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,

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

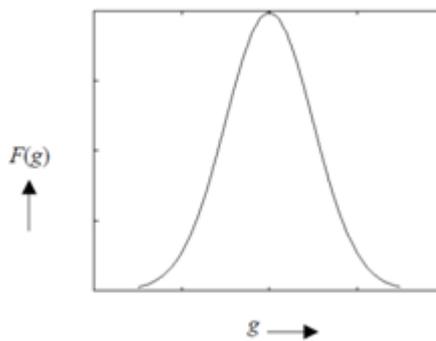


Figure: 2 Gaussian Noise

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 Figure 2.

- Salt-and-pepper noise

An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by analog-to-digital converter errors, bit errors in transmission, etc. Dead pixels in an LCD monitor produce a similar, but non-random, display. This can be eliminated in large part by using dark frame subtraction and by interpolating around dark/bright pixels. Salt and pepper noise is an impulse type of noise, which is also referred to as intensity spikes. 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.

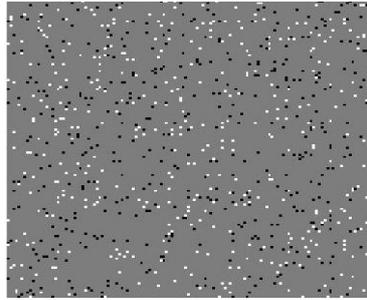


Figure:3 Salt and Pepper noise

- *Shot noise*

The dominant noise in the lighter parts of an image from an image sensor is typically that caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level; this noise is known as photon shot noise. Shot noise has a root-mean-square value proportional to the square root of the image intensity, and the noises at different pixels are independent of one another. Shot noise follows a Poisson distribution, which is usually not very different from Gaussian.

In addition to photon shot noise, there can be additional shot noise from the dark leakage current in the image sensor; this noise is sometimes known as "dark shot noise" or "dark-current shot noise". Dark current is greatest at "hot pixels" within the image sensor; the variable dark charge of normal and hot pixels can be subtracted off (using "dark frame subtraction"), leaving only the shot noise, or random component, of the leakage; if dark-frame subtraction is not done, or if the exposure time is long enough that the hot pixel charge exceeds the linear charge capacity, the noise will be more than just shot noise, and hot pixels appear as salt-and-pepper noise.

- *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:

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

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 figure. The gamma distribution is given below in Figure 3.

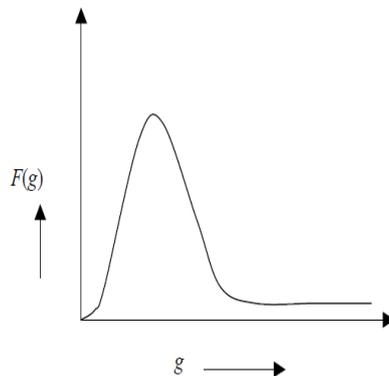


Figure:3 Gamma distribution

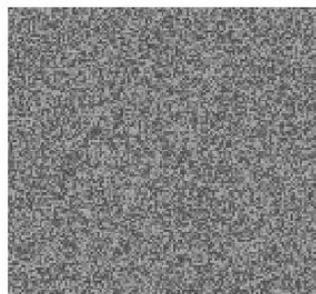


Figure:4 Speckle noise

Classification of different denoising techniques:

There are two there are two basic approaches to image denoising, spatial filtering methods and transform domain filtering methods.

1. 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.

1.1 Non linear filter

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 [8], rank conditioned rank selection [9], and relaxed median [10] have been developed to overcome this drawback.

- *Median filter*

Like the mean filter, the median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighbouring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighbourhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighbourhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.)

- *Weighted median filter*

This filter uses a new impulse detector, which is based on the differences between the current pixel and its neighbours aligned with four main directions. After impulse detection, it does not simply replace noisy pixels identified by outputs of median filter but continue to use the information of the four directions to weight the pixels in the window in order to preserve the details as removing noise. First it considers a 5X5 window. Now it considers the four directions: horizontal, vertical and two diagonal. Each direction there is 5 pixel points. It then calculates the weighted difference in each direction and takes the minimum of them. The minimum value is compared with a threshold value and if it is greater than the threshold value then it is a noisy pixel otherwise not. In filtering phase, it calculates the standard deviation in four directions. Because the standard deviation describes how tightly all the values are clustered around the mean in the set of pixels shows that the four pixels aligned with this direction are the closest to each other. Therefore, the center value should also be close to them. Now it calculates the weighted median, giving extra weight on that direction in which direction standard deviation is small and replaces the noisy pixel with this median value.

1.2 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. 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 base denoising scheme in [12, 13].

- *Mean filter*

The idea of mean filtering is simply to replace each pixel value in an image with the mean ('average') value of its neighbours, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean. Often a 3x3 square kernel is used, although larger kernels (e.g. 5x5 squares) can be used for more severe smoothing.

- *Weiner filter*

The Wiener filter purpose is to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal. It is based on a statistical approach. Typical filters are designed for a desired frequency response. The Wiener filter approaches filtering from a different angle. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the LTI filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following:

Assumption: signal and (additive) noise are stationary linear stochastic, processes with known spectral characteristics or known autocorrelation and cross correlation.

Requirement: the filter must be physically realizable, i.e. causal (this requirement can be dropped, resulting in a non-causal solution).

Performance criteria: minimum mean-square error.

2. Transform Domain Filtering

The transform domain filtering methods can be subdivided according to the choice of the basis functions. The basis functions can be further classified as data adaptive and non-adaptive. Non-adaptive transforms are discussed first since they are more popular.

2.1 Spatial-Frequency Filtering

Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods [14] the removal of the noise is achieved by designing a frequency domain filter and adapting a cut-off frequency when the noise components are decorrelated from the useful signal in the frequency domain. These methods are time consuming and depend on the cut-off frequency and the filter function behavior.

2.2 Wavelet domain

Filtering operations in the wavelet domain can be adaptive filtering and non adaptive threshold filtering techniques .

2.2.1 Non Adaptive threshold

VISU Shrink [15] is non-adaptive universal threshold, which depends only on number of data points. It has asymptotic equivalence suggesting best performance in terms of MSE when the number of pixels reaches infinity. VISU Shrink is known to yield overly smoothed images because its threshold choice can be unwarrantedly large due to its dependence on the number of pixels in the image

2.2.2 Adaptive threshold

SUREShrink [15] uses a hybrid of the universal threshold and the SURE [Stein's Unbiased Risk Estimator] threshold and performs better than VISUShrink. BayesShrink [16, 17] minimizes the Bayes' Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptive threshold. BayesShrink outperforms SUREShrink most of the times. Cross Validation [18] replaces wavelet coefficient with the weighted average of neighborhood coefficients to minimize generalized cross validation (GCV) function providing optimum threshold for every coefficient. The assumption that one can distinguish noise from the signal solely based on coefficient magnitudes is violated when noise levels are higher than signal magnitudes. Under this high noise circumstance, the spatial configuration of neighboring wavelet coefficients can play an important role in noise-signal classifications. Signals tend to form meaningful features (e.g. straight lines, curves), while noisy coefficients often scatter randomly.

IV. CONCLUSIONS

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 recover the noisy image. Different filters show different results after filtering .Some filters degrade image quality and remove edges. Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) as well as in terms of visual quality of the images.

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