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De-Noising Techniques: A Comparative Approach

Supriya Tiwari[1], Nitin Naiyar[2]

[1]Lecturer, Rungta College of Engineering and Technology, Bhilai, Chhattisgarh, India

[2]Reader, Rungta College of Engineering and Technology, Bhilai, Chhattisgarh, India

Abstract: ***Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age. Whatever may be the way of transmission, the data tends to get noisy and thereby the further processing does not lead to good results. Hence, it is very essential to keep the data close to originality. The received image needs processing before it can be used in applications. Image de-noising involves the manipulation of the image data to produce a visually high quality image. This paper reviews the existing de-noising algorithms, such as filtering approach; wavelet based approach, and performs their comparative study. Selection of the de-noising algorithm is application dependent. Hence, it is necessary to have knowledge about the noise present in the image so as to select the appropriate de-noising algorithm.***

Keywords: Noise, De-noising, Filtering, Wavelet

1. Introduction

In many applications, image de-noising is used to produce good estimates of the original image from noisy observations. The restored image should contain less noise than the observations while still keep sharp transitions (i.e. edges). Generally noise is introduced in the image during image transmission. The added noise will be of various kinds like additive random noise (Gaussian noise), salt and pepper noise, etc. Depending on the type of the noise, the degradation of the image will vary. According to the percentage of image quality degradation, the noise removal techniques must be chosen. Image de-noising is the problem of finding a clean image, given a noisy one. Hence image de-noising is a decomposition problem. The goal of image de-noising methods is to recover the original image from a noisy measurement,

$v(i) = u(i) + n(i),$

where $v(i)$ is the observed value, $u(i)$ is the “true” value and $n(i)$ is the noise perturbation at a pixel i.

2. Types of Noise

Noise can broadly be classified in two types:

2.1 Additive Noise

An additive noise follows the rule

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

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.

2.2 Multiplicative Noise

The multiplicative noise satisfies
$w(x, y) = s(x, y) \times n(x, y)$,

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.

2.3 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,

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

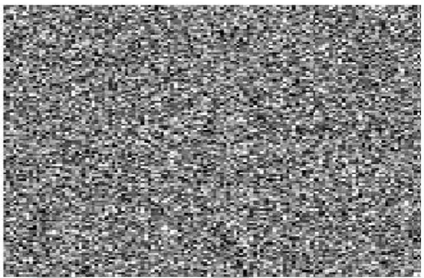


Figure 2.3

The figure 2.1 shows Gaussian noise with mean=0, variance 0.05

where g represents the gray level, m is the mean or average of the function, and σ is the standard deviation of the noise.

2.4 Salt and Pepper Noise

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. 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.

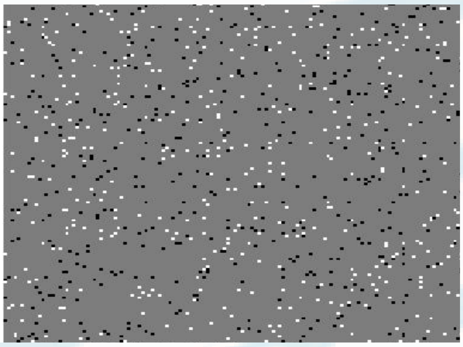


Figure 2.4

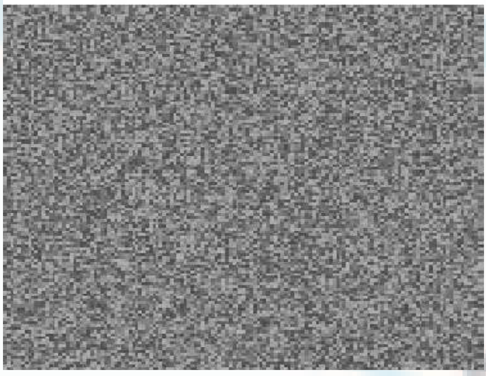
Salt and pepper noise with a variance of 0.05 is shown in the figure 2.2.

2.5 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 $a2\alpha$ and g is the gray level.



Figur 2.5

On an image, speckle noise (with variance 0.05) looks as shown in figure 2.5

2.6 Brownian Noise

Brownian noise 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. On an image, Brownian noise would look like the image shown in figure 2.4

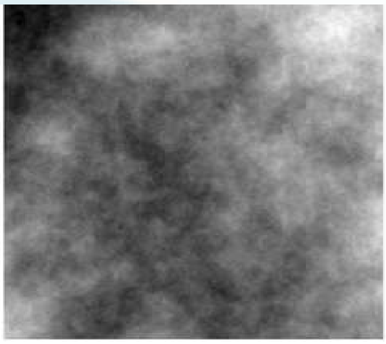


Figure 2.6

3. Linear and Non-linear Filtering

Linear filtering using mean filter and Least Mean Square (LMS) adaptive filter and nonlinear filtering based on median filter are discussed below.

3.1 Mean Filter

A mean filter acts on an image by smoothing it; that is, it reduces the intensity variation between adjacent pixels [7]. 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 mean or average filter works on the shift-multiply-sum principle. The mean filter is used in applications where the noise in certain regions of the image needs to be removed. In other words, the mean filter is useful when only a part of the image needs to be processed.

3.2 LMS Adaptive Filter

An adaptive filter does a better job of de-noising 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 de-noising non-stationary images, that is, 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. Similar to the mean filter, the LMS adaptive filter works well for images corrupted with salt and pepper type noise. But this filter does a better de-noising job compared to the mean filter.

3.3 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 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. The median is more robust compared to the mean. Thus, a single very unrepresentative pixel in a neighborhood will not affect the median value significantly. Since the median value must actually be the value of one of the pixels in the neighborhood, the median filter does not create new unrealistic pixel values when the filter straddles an edge. For this reason the median filter is much better at preserving sharp edges than the mean filter. These advantages aid median filters in de-noising uniform noise as well from an image.

4. Wavelet Transforms and De-noising

4.1 Wavelet Transform

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. Wavelets are generally much more concentrated in time. They usually provide an analysis of the signal which is localized in both time and frequency. Given a mother wavelet ψ(t) (which can be considered simply as a basis function of L2). The continuous wavelet transform (CWT) of a function x(t) (assuming that x ∈ L2) is defined as:

$$X(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi\left(\frac{t-b}{a}\right) x(t)\,dt$$

The scale or dilation parameter corresponds to frequency information, and the translation parameter b relates to the location of the wavelet function as it is shifted through the signal, so it corresponds to the time information in the transform. From the integral it can be seen as a convolution operation of the signal and a basis function ψ(t) (up to dilations and translations). In practice, the transform which is used is the discrete wavelet transform (DWT) which transforms discrete (digital) signals to discrete coeﬃcients in the wavelet domain. This transform is essentially a sampled version of CWT. Instead of working with a,b ∈R, the values of X (a,b) are calculated over a discrete grid:

$$a=2^{-j},\ b=k.2^{-j},\ j, k \in Z$$

where this type of discretization is called dyadic dilation and dyadic position.

4.2 Wavelet Thresholding

Wavelet coefficients calculated by a wavelet transform represent change in the time series at a particular resolution. By considering the time series at various resolutions, it is then possible to filter out noise. The term wavelet thresholding is explained as decomposition of the data or the

Image into wavelet coefficients, comparing the detail coefficients with a given threshold value, and shrinking these coefficients close to zero to take away the effect of noise in the data. The image is reconstructed from the modified coefficients. This process is also known as the inverse discrete wavelet transform. During thresholding, a wavelet coefficient is compared with a given threshold and is set to zero if its magnitude is less than the threshold; otherwise, it is retained or modified depending on the threshold rule. Thresholding distinguishes between the coefficients due to noise and the ones consisting of important signal information.

The choice of a threshold is an important point of interest. It plays a major role in the removal of noise in images because de-noising most frequently produces smoothed images, reducing the sharpness of the image. Care should be taken so as to preserve the edges of the de-noised image. There exist various methods for wavelet thresholding, which rely on the choice of a threshold value there are two basic types of thresholding.

1. **Hard Thresholding:** It refers to the procedure where the input elements with absolute value lower than the set threshold value, are set to zero. It is discontinuous at the point where |x| = thld and yields abrupt artifacts in the recovered images especially when the noise energy is significant.

   x= (abs(y) > thld) . * y)

2. **Soft Thresholding:** It refers to the procedure where firstly the input elements with value lower than the set threshold value, are set to zero and are then scaled to the non-zero coefficients toward zero. It eliminates Discontinuity and gives more visually pleasant images.

   x= abs (y)
   x= sign (y).* (x ≥ thld).* (x-thld)

4.3 VisuShrink

VisuShrink is thresholding by applying the Universal threshold proposed by Donoho and Johnstone [2]. This threshold is given by $\sigma\sqrt{2logM}$ where σ is the noise variance and M is the number of pixels in the image. With high probability, a pure noise signal is estimated as being identically zero. However, for de-noising images, VisuShrink is found to yield an overly smoothed estimate. This is because the universal threshold (UT) is derived under the constraint that with high probability, the estimate should be at least as smooth as the signal. So the UT tends to be high for large values of M, killing many signal coefficients along with the noise. Thus, the threshold does not adapt well to discontinuities in the signal.

4.4 SureShrink

SureShrink is a thresholding by applying sub-band adaptive threshold, a separate threshold is computed for each detail sub-band based upon SURE (Stein's unbiased estimator for risk), a method for estimating the loss. This method specifies a threshold value t_j for each resolution level j in the wavelet transform which is referred to as level dependent thresholding. The goal of SureShrink is to minimize the mean squared error. SureShrink suppresses noise by thresholding the empirical wavelet coefficients. The SureShrink threshold t* is defined as

$$t^* = \min(t, \sigma\sqrt{2logM})$$

where t denotes the value that minimizes Stein's Unbiased Risk Estimator, σ is the noise variance and M is the size of the image.

4.5 BayesShrink

BayesShrink [5] is an adaptive data-driven threshold for image de-noising via wavelet soft-thresholding. The threshold is driven in a Bayesian framework, and we assume generalized Gaussian distribution (GGD) for the wavelet coefficients in each detail sub-band and try to find the threshold T which minimizes the Bayesian Risk. The reconstruction using BayesShrink is smoother and more visually appealing than one obtained using SureShrink.

5. Result

SNR values of filtering approaches are given below;

Method	*SNR of input*	*SNR of output*	*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
LMS Adaptive Filter	18.88	28.01	Salt and Pepper, 0.05
LMS Adaptive Filter	13.39	22.40	Gaussian, 0.05
Median Filter	18.88	47.97	Salt and Pepper, 0.05
Median Filter	13.39	22.79	Gaussian, 0.05

SNR values of Wavelet Transform approach;

Method	*SNR of input*	*SNR of output*	*Noise type and Variance, σ*
VisuShrink	13.39	31.17	Salt and Pepper, 0.05
VisuShrink	13.39	19.01	Gaussian, 0.05
SureShrink	18.88	36.46	Salt and Pepper, 0.05
SureShrink	13.39	40.67	Gaussian, 0.05
BayesShrink	18.88	30.98	Salt and Pepper, 0.05
BayesShrink	13.39	18.92	Gaussian, 0.05

6. Conclusion

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 and LMS adaptive filter. It produces the maximum SNR for the output image compared to the linear filters considered. The LMS adaptive filter proves to be better than the mean filter but has more time complexity.

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 and BayesShrink. However, the output from BayesShrink method is much closer to the high image and there is no blurring in the output image unlike the other two methods. VisuShrink cannot denoise multiplicative noise unlike BayesShrink. It has been observed that BayesShrink is not effective for noise variance higher than 0.05. De-noising salt and pepper noise using VisuShrink and BayesShrink has proved to be inefficient. Since selection of the right denoising procedure plays a major role, it is important to experiment and compare the methods.

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