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Review Article

Noise Reduction: A Comparative Study of Different Filters

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Abstract

In modern data communication network sending visual digital images is a major issue. The image sent from the source may not be received properly by the receiver and may get corrupted with noise. Thus image needs processing before it can be used in various applications. Noise reduction in image involves the manipulation of the image data to produce a high quality image. The current paper have discussed different noise reduction techniques such filtering approach and wavelet approach for removing various noise present in images. The paper will discuss various noises such as Gaussian noise, Salt and Pepper noise, Speckle noise and Brownian noise.

Keywords: *Noise Reduction, Filtering, Wavelet, Salt and Pepper noise, Gaussian noise, Speckle noise, Brownian noise.*

1. Introduction

In digital images noise reduction is the severe problem and thus is a concern of diverse application areas. Noise reduction is necessary to retain image in its best quality. Degradation in images comes due to blurring as well as noise due to photometric and electronic sources. Blurring is a form of bandwidth reduction of the image caused by imperfect formation of image e.g. relative motion between the camera and the original scene is out of focus. Noise reduction is used in fields such as astronomy where the resolution limitations are severe, in medical images where the requirement for high quality imaging are needed for diagnosis, and in forensic science where potentially useful photographic evidence is sometimes corrupted due to noise.

2. Different types of noise

2.4 Impulsive or Salt Pepper Noise

Impulsive noise is also known as salt and pepper noise which can appear when the sensor that picks up the image is saturated and the value of the pixel shows a high value or when the signal is lost and the pixel shows a low value. In this case, the image has too high or too low pixel values (Asoke Nath, 2013). This noise occurs due to errors in data. The salt and pepper noise is shown in fig.1 and probability density function is shown in fig.2.

2.2 Gaussian Noise

Gaussian noise shows little variation in the image for some reasons such as different sensor gain, quantization errors in digitization, etc. and is evenly distributed over the signal. Gaussian noise distribution is a bell shaped probability distribution function (pdf) (Asoke Nath 2013).

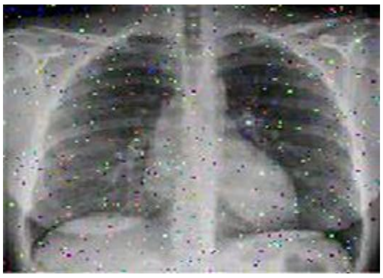

Fig.1 Salt and Pepper Noise

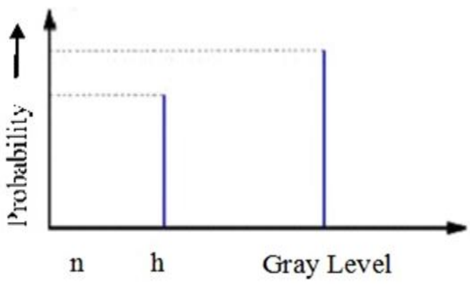

Fig.2 Probability density function of Salt and Pepper noise

Gaussian noise is distributed evenly over the signal, i.e., each pixel in the noisy image is the sum of true pixel value and a value of random Gaussian distributed noise. Probability Distribution Function (pdf) of Gaussian noise is given as:

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

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Where, $F(x)$ is Probability Distribution Function (pdf) and is standard deviation.

The Gaussian noise is shown in fig.3 and the graphical representation of Gaussian noise is shown in fig.4.

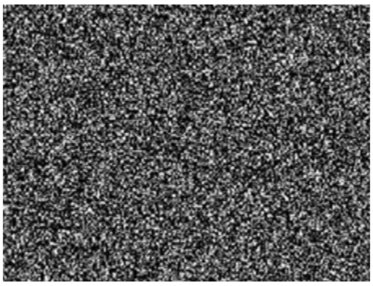

Fig.3 Gaussian noise

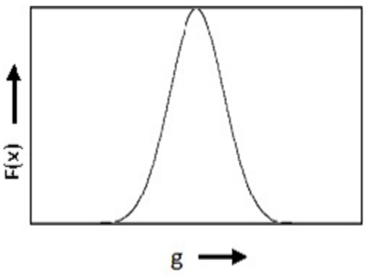

Fig.4 Gaussian noise distribution

2.3 Speckle Noise

Speckle Noise is a multiplicative noise, which occurs in almost all coherent imaging systems such as laser, acoustics and SAR (Synthetic Aperture Radar) imagery. The source of this noise is allocated to random interference between the coherent returns. Speckle noise have characteristics of multiplicative noise and follows gamma distribution (Asoke Nath 2013), given as:

$$F(g) = \frac{g^{a-1}}{(a-1)!a^{a}} e^{-\frac{g}{a}} \qquad (2)$$

Where, a is variance and g is gray scale.

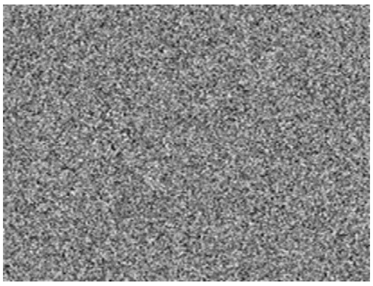

Fig.5 Speckle noise

2.1 Brownian Noise

Brownian noise (Asoke Nath 2013) is categorized as fractal or 1/f noise. Fractal Brownian motion is called the mathematical model for 1/f noise. Fractal Brownian motion for 1/f noise is a non- stationary stochastic process that follows the normal distribution. Brownian noise can be obtained by integrating white noise.

The Brownian noise is shown in fig.6 and the Brownian noise distribution is shown in fig.7.

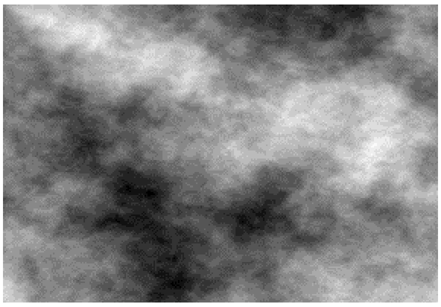

Fig.6 Brownian noise

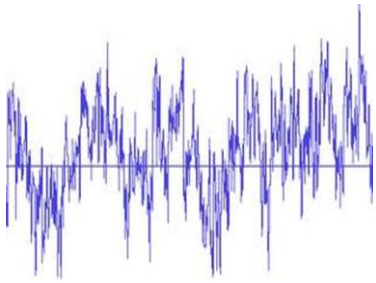

Fig.7 Brownian noise distribution

3. Different filters and transform

3.1 Adaptive Weighted Median Filter (AWMF)

The adaptive weighted median filter (AWMF) is an enhanced median filter. AWMF introduce the concept of weighting coefficient for the pixels in window. The coefficient effects every pixel in such a way that its value appears as many times as the weights in the calculation of the median indicates. Thus, if the weights are the same, this method will behave as median filter, but, if the weights are not the same and they decrease from the center of the window to the outer limits, the details and the edges of the image will be less changed. At the same time, less noise will be removed.

3.2 Butterworth Filter

Butterworth filter have the property of maximally flat frequency response and no ripples in the pass band. It rolls of towards zero in the stop band and its response slopes off linearly towards negative infinity on logarithmic Bode Plot. Butterworth filters have monotonically changing magnitude function with frequency. The response of Butterworth low pass filter is:

$$H(j\Omega) = \frac{A}{\left[1+(\frac{\Omega}{\Omega_c})^{2N}\right]^{0.5}} \qquad (3)$$

Where, A is the filter gain and Ω_c is the 3 dB cut-off frequency and N is the order of the filter.Ω is the frequency of filter.

3.3 Ideal Filter

Ideal filters allow a specified frequency range to pass through while attenuating a specified unwanted frequency range. The ideal filter is impossible to realize without having signals of infinite extent in time, and so needs to be approximated for real ongoing signals, because the sinc function's support region extends to all past and future times. The ideal filter need to have infinite delay, or knowledge of the infinite future and past, in order to perform the convolution.

3.4 Homomorphic Filter

Homomorphic filtering is used to remove multiplicative noise. In homomorphic filtering firstly, the multiplicative components are converted to additive noise components by moving to log domain. The expression for Homomorphic filtering is given as:

$$log\, f(x,y) = log\ (g(x,y)\eta_m(x,y)) \tag{4}$$

$$log\, f(x,y) = log\ \big(g(x,y)\big) + log\ (\eta_m(x,y)) \tag{5}$$

Where, $f(\boldsymbol{x},\boldsymbol{y})$ is the real noise image, $\boldsymbol{g}(\boldsymbol{x},\boldsymbol{y})$ represents an unknown noise-free image and $n_m(x,y)$is multiplicative noise function. Then the signal is passed through the linear filter and then inverse homomorphic transform gives the noise free image. In homomorphic filtering sequence (Robert W. Ives et. al) components which have been multiplied are converted into components that are added by taking the Fourier transform followed by the logarithm, shown in fig-8. After linear filtering, to separate the added components anti-logarithm and inverse Fourier transform are applied to the image.

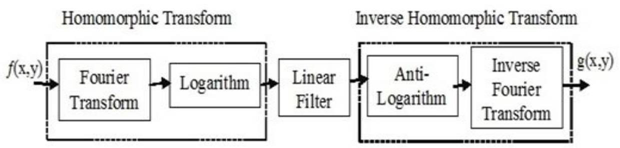

Fig.8 Homomorphic Filter

3.5 Wavelet Transform

The frequency representation of input signal is obtained with transform. In the wavelet transform the function is expressed in the form of small wave called wavelet. Previous techniques of thresholding includes filtering in spatial domain for analysis, however, in wavelet transform, the complete analysis is done in frequency domain having both time – scale aspects. Wavelet thresholding (Supriya Tiwari et. al) is explained as the decomposition of the image into wavelet coefficients and comparing the detail coefficients close to zero to remove the noise from the image. Wavelet thresholding (Supriya Tiwari et. al) are hard thresholding and soft thresholding. Hard threshold is a "keep or kill" procedure and seems appealing. The soft thresholding shrinks coefficients above the threshold in absolute value. Soft thresholding makes algorithms mathematically more tractable. Moreover, hard thresholding does not even work with some algorithms such as the GCV procedure. Sometimes, pure noise coefficients may pass the hard threshold and appear as 'blips' in the output and thus produce false structures. Soft thresholding shrinks these false structures (blips).

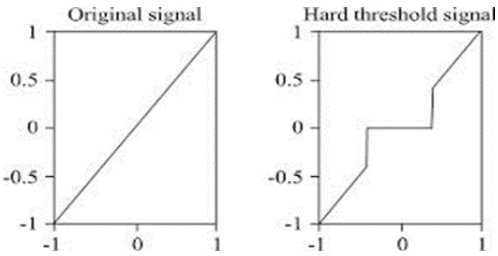

Fig.8 Hard Thresholding

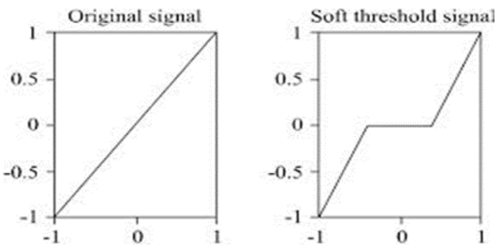

Fig.9 Soft Thresholding

3.6 Weiner Filter

Wiener filter remove the noise that has corrupted a signal. Wiener filter is based on a statistical approach. Wiener filters are characterized by the following:

A. Assumption: signal and (additive) noise are stationary linear random processes with known spectral characteristics.
B. Requirement: the filter must be physically realizable, i.e. causal (this requirement can be dropped, resulting in a non-causal solution).
C. Performance criteria: minimum mean-square error.

4. Literature Review

Robert W. Ives et al. (2003) proposed speckle reduction of SAR imagery using homomorphic processing and predictive filtering.

Khalifa Dejmal et al. (2005) proposed speckle deduction in ultrasound images by minimization of total variation.

J. R. Sanchez et al. (2009) proposed a method aiming at speckle reduction in ultrasound data by means of frequency compounding (FC) and coded excitation and pulse–compression technique called resolution enhancement compression (REC).

Xiwen Qin et al. (2010) developed an improved thresholding function to reduce the fixed-bias of the soft thresholding technique.

Milindkumar V. Sarode et al. (2011) proposed reduction of speckle noise and image enhancement of images using filtering technique.

Asoke Nath et al. (2013) proposed the comparative study of different additive noise models and also multiplicative noise models such as Gaussian noise, salt and pepper noise, speckle noise and Brownian noise.

Gurmeet Kaur et al. (2013) proposed performance evaluation of various image de-noising techniques.

Vikas Gupta et al. (2013) proposed image deoising using wavelet transform method.

Supriya Tiwari et al. (2014) proposed de-noising techniques comparison.

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