Survey Study of Image Denoising Techniques

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Abstract: **These papers presents a survey on various noises and image denoising techniques and discuss these techniques and filters in detail. Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form.**

I INTRODUCTION

A very large portion of digital image processing is devoted to image restoration. This includes research in algorithm development and routine goal oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained. Degradation comes from blurring as well as noise due to electronic and photometric sources. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contribute to the degradation.

Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form.

An image is often corrupted by noise in its acquition and transmission. Image denoising is used to remove the additive noise while retaining as much as possible the important signal features. In the recent years there has been a fair amount of research on wavelet thresholding and threshold selection for signal de-noising, because wavelet provides an appropriate basis for separating noisy signal from the image signal. The motivation is that as the wavelet transform is good at energy compaction, the small coefficient are more likely due to noise and large coefficient due to important signal features. These small coefficients can be threshold without affecting the significant features of the image.

Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept or modified. Replacing the small noisy coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with the essential signal characteristics and with less noise.

Since the work of Donoho & Johnstone , there has been much research on finding thresholds, however few are specifically designed for images.

Here we discuss the three approaches of Image denoising which are:

1. **Filter based**
2. **Wavelet Analysis**
3. **Principal Component Analysis based**

*A Types of noise***:**

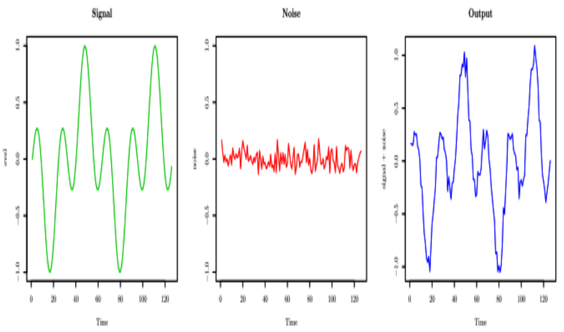
Any real world sensor is affected by a certain degree of noise, whether it is thermal, electrical or otherwise. This noise will corrupt the true measurement of the signal, such that any resulting data is a combination of signal and noise.

Additive noise, probably the most common type, can be expressed as:

$$I(t) = S(t) + N(t) \text{.........................} \quad (1)$$

where $I(t)$ is the resulting data measured at time t, $S(t)$ is the original signal measured, and $N(t)$ is the noise introduced by the sampling process, environment and other sources of interference.

A simple example of a pure 1-Dimensional input signal is shown in Figure 1(a). This signal is affected by environmental noise (shown in Figure 1(b)) and the resulting data output from the sensor is the corrupted signal in Figure 1(c).



1.(a) 1.(b) 1.(c)

Two of the most common types of noise in image processing are Gaussian noise and Impulse noise (also known as “salt and pepper” noise).

(i) *Additive Gaussian Noise*: In Gaussian noise models, the noise density follows a Gaussian normal distribution $G(\bar{x}, \sigma)$ defined by the mean $\bar{x}$ and standard deviation σ. example. At each input voxel vin, a sample is taken from the normal variate distribution G(d), and added to the image to produce. for some mean noise $\bar{x}$ and standard deviation σ. The seed d is an arbitrary number to start the pseudo-random sequence. For applications that require high entropy, a common technique is to seed with the current system time (in milliseconds)

(ii) *Additive and Multiplicative Noises*: Noise is an 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:

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

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. 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.

(iii) *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.

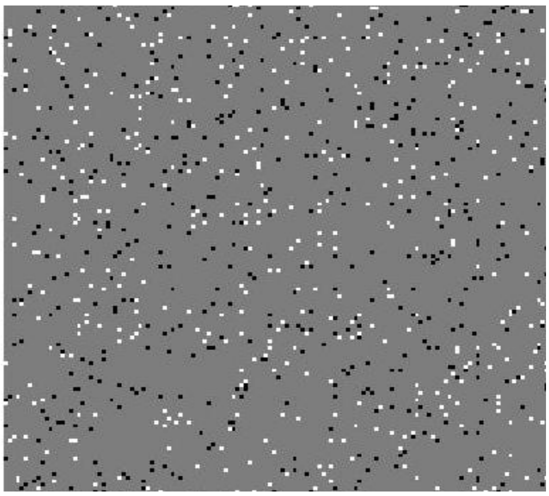


Fig 2. Image effected by Salt n pepper noise

(iv) *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:

where variance is *a2α and g is the gray level.*

On an image, speckle noise (with variance 0.05) looks as:

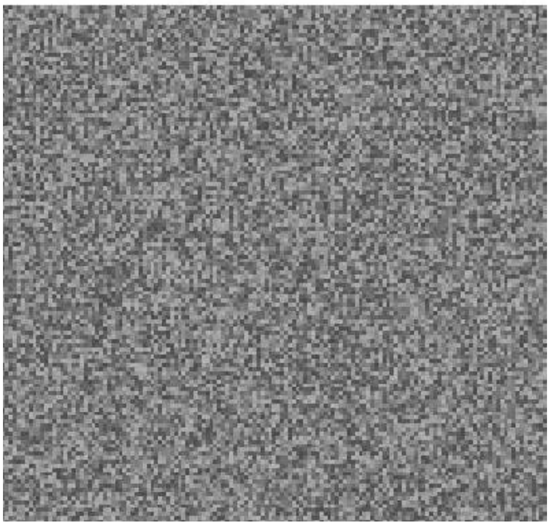


Fig 3. Image effected by Speckle noise

B Filter Based Image de-noising:

1. Linear Filter
2. Non-Linear Filter

(i) Linear Filtering

(a) Mean Filter : A mean filter [Um98] acts on an image by smoothing it; that is, 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 itself. 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 3× 3 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.

Image 4.1 is the one corrupted with salt and pepper noise with a variance of 0.05.The output image after Image 4.1 is subjected to mean filtering is shown in Image 4.2.

It can be observed from the output that the noise dominating in Image 4.1 is reduced in Image 4.2. The white and dark pixel values of the noise are changed to be closer to the pixel values of the surrounding ones. Also, the brightness of the input image remains unchanged because of the use of the mask, whose coefficients sum up to the value one.

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.

Fig 4.1 Image with noise
Fig 4.2 Mean Filtered Image

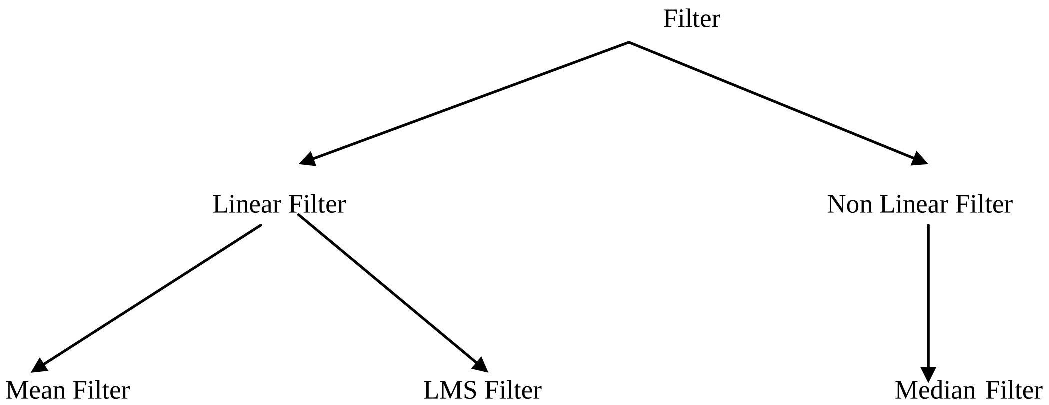


Fig 5. Filter classification

(b) LMS Adaptive Filter: An adaptive filter 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, 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 [Li93]. 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. Compared to other adaptive filters, the Least Mean Square (LMS) adaptive filter is known for its simplicity in computation and implementation. The basic model is a linear combination of a stationary low-pass image and a non-stationary high-pass component through a weighting function [Li93]. Thus, the function provides a compromise between resolution of genuine features and suppression of noise.

The LMS adaptive filter incorporating a local mean estimator [Li93] works on the following concept.

A window, W, of size m×n is scanned over the image. The mean of this window, μ, is subtracted from the elements in the window to get the residual matrix Wr

$$W\,r = W - \mu$$

The largest eigenvalue λ of the original window is calculated from the autocorrelation matrix of the window considered. The use of the largest eigenvalue in computing the modified weight matrix for the next iteration reduces the minimum mean squared error. A value η is selected such that it lies in the range (0, 1/λ). In other words,

$$0 < \eta < 1/\lambda.$$

When the image is corrupted with salt and pepper noise, it looks as shown in Image 6.1. When Image 6.1 is subjected to the LMS adaptive filtering, it gives an output image shown in Image 6.2. 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 denoising job compared to the mean filter.

Fig 6.1 Image with noise
Fig 6.2 LMS filtered image

(ii) Non-Linear Filtering

(a) *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 3× 3, 5× 5, or 7× 7 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. Note that the median value must be written to a separate array or buffer so that the results are not corrupted as the process is performed. Figure 7 illustrates the methodology

123	**125**	**126**	**130**	**140**
122	**124**	**126**	**127**	**135**
118	**120**	**150**	**125**	**134**
119	**115**	**119**	**123**	**133**
111	**116**	**110**	**120**	**130**

Neighborhood values:
115,119,120,123,124,125,126,127,150
Median value: 124

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 denoising uniform noise as well from an image.

As mentioned earlier, the image “cameraman.tif” is corrupted with salt and pepper noise with with salt and pepper noise and is given to the median filter filtering. The window specified is of size 3×3. Image is the output after median filtering. It can be observed that the edges are preserved and the quality of denoising is much better compared to the Images.

Fig 8.1 Image with noise

Fig 8.2 Median Filtered Image

(c) Wavelet Based Image de-noising process

Donohue and Johnstone pioneered the work on filtering of additive Gaussian noise using wavelet thresholding. From their properties and behavior, wavelets play a major role in image compression and image denoising. Since our topic of interest is image denoising, the latter application is discussed in detail. 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 denoising most frequently produces smoothed images, reducing the sharpness of the image. Care should be taken so as to preserve the edges of the denoised image. There exist various methods for wavelet thresholding, which rely on the choice of a threshold value. Some typically used methods for image noise removal include VisuShrink, SureShrink and BayesShrink [An01, Ch00, Do94].

Prior to the discussion of these methods, it is necessary to know about the two general categories of thresholding. They are hard- thresholding and soft-thresholding. In practice, it can be seen that the soft method is much better and yields more visually pleasant images. This is because the hard method is discontinuous and yields abrupt artifacts in the recovered images. Also, the soft method yields a smaller minimum mean squared error compared to hard form of thresholding. Now let us focus on the three methods of thresholding mentioned earlier. For all these methods the image is first subjected to a discrete wavelet transform, which decomposes the image into various sub-bands.

Let

$$f = \{fij, \text{i, j} = 1,2\ldots\text{M}\}$$

denote the M×M matrix of the original image to be recovered and M is some integer power of 2. During transmission the signal f is corrupted by independent and identically distributed (i.i.d) zero mean, white Gaussian Noise nij with standard deviation σ i.e. $nij \sim N(0, \sigma 2)$ and at the receiver end, the noisy observations

$$gij = fij + \sigma\, nij$$

is obtained. The goal is to estimate the signal f from noisy observations gij such that Mean Squared error (MSE)[11] is minimum. Let W and W-1 denote the two dimensional orthogonal discrete wavelet transform (DWT) matrix and its inverse respectively.

Fig 9.1 Image with noise
Fig 9.2 Normal shrink filtered Image

II LITERATURE SURVEY

1. B.Asad, et.al, "An Analytical Method to Compare Image Processing Filters for 3D Reconstruction of Ultrasonic Images", Proceedings of the 2007 IEEE International Conference on Mechatronics and Automation August 5 - 8, 2007, Harbin, China

Precise 3D reconstructions of 2D ultrasonic images are important for robot navigation. In this Paper a new analytical method to select the best image processing filters for 3D reconstruction of ultrasonic has been proposed .It is based on four goals: signal to noise enhancement, errors caused by filters in 2D images and 3D shapes and visual appearance. It is found the Adaptive Nonlocal Filtering (OFS) has the best quality in aspect of error in 2D and 3D features and promoting signal to noise. The analytical method has been examined by real ultrasonic images of patients and simulated images made by Field II. It is suggested to use OFS filter for robust ultrasonic 3D reconstruction .

2. A switching median filter with boundary discriminative noise detection for extremely corrupted images by Pei-Eng Ng; Kai-Kuang Ma**;**

A novel switching median filter incorporating with a powerful impulse noise detection method, called the boundary discriminative noise detection (BDND), is proposed in this paper for effectively denoising extremely corrupted images. To determine whether the current pixel is corrupted, the proposed BDND algorithm first classifies the pixels of a localized window, centering on the current pixel, into three groups-lower intensity impulse noise, uncorrupted pixels, and higher intensity impulse noise. The center pixel will then be considered as "uncorrupted," provided that it belongs to the "uncorrupted" pixel group, or "corrupted." For that, two boundaries that discriminate these three groups require to be accurately determined for yielding a very high noise detection accuracy-in our case, achieving zero miss-detection rate while maintaining a fairly low false-alarm rate, even up to 70% noise corruption. Four noise models are considered for performance evaluation. Extensive simulation results conducted on both monochrome and color images under a wide range (from 10% to 90%) of noise corruption clearly show that our proposed switching median filter substantially outperforms all existing median-based filters, in terms of suppressing impulse noise while preserving image details, and yet, the proposed BDND is algorithmically simple, suitable for real-time implementation and application (2009).

3. Modified Adaptive Center Weighted Median Filter for Suppressing Impulsive Noise in Images by B.GHANDEHARIAN, H.SADOGHI YAZDI and F.HOMAYOUNI, International Journal of Research and Reviews in Applied Sciences (2009)

A new switch median filter is presented for suppression of impulsive noise in image. The proposed filter is Modified Adaptive Center Weighted Median (MACWM) filter with an adjustable central weight obtained by partitioning the observation vector space. Dominant points of the proposed approach are partitioning of observation vector space using clustering method, training procedure using LMS algorithm then freezing weights in each block are applied to test image. The proposed method includes fuzzy clustering part for clustering the observed vector of each pixel into one of M mutually exclusive blocks. In the training phase, Least Mean

Square (LMS) algorithm use to train center weight in each block then obtained weights used in testing phase. Final results shows better performance in the impulse noise reduction over standard images relative the median (MED) filter, the switching scheme I (SWM-I) filter, the signal dependent rank order mean (SD-ROM) filter, the tristate median (TSM) filter, the fast peer group filter (FPGF), the fuzzy median (FM) filter, the PFM filter and the adaptive center weighted median (ACWM) filter.

III CONCLUSION

We have presented a survey on various noises and image denoising techniques and discuss these techniques and filters in detail.

Various kind of noises are:

1. Additive Gaussian Noise
2. Additive and Multiplicative Noises
3. Salt and Pepper Noise
4. Speckle Noise

We discuss the three approaches of Image denoising which are:

1. Filter based
2. Wavelet Analysis
3. Principal Component Analysis based

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