A Review and Comprehensive Comparison of Image Denoising Techniques

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***Abstract*— Removing noise from the original signal is still a challenging problem for researchers. Despite the complexity of the recently proposed methods, most of the algorithms have not yet attained a pleasing level of applicability. This paper presents a review of some significant work in the area of image denoising. After a brief introduction, some of the popular approaches are categorized into different sets. Within each category, several representative algorithms are selected for evaluation and comparison. The experimental results are discussed and analyzed to determine the overall advantages and disadvantages of each category. Insights and potential future work in the area of denoising are also discussed.**

Keywords— Adaptive filter, image denoising, spatial filter, threshold, transform domain, wavelet domain.

I. INTRODUCTION

Image denoising plays an important role both in daily routine such as satellite television, computer tomography, magnetic resonance imaging as well as in area of research serving as the actual foundation for many applications such as object recognition and technology such as geographical information systems, astronomy. As the number of image sensors per unit area increases, data sets collected by image sensors are contaminated by noise due to imperfect instruments, interfering natural phenomenon can all degrade the quality of data of interest. Noise can also be introduced in images by transmission and compression. Thus, image denoising is often a necessary and pre-processing step for image analysis. So, it is necessary to apply an efficient denoising technique to compensate for such type of corruption.

Image denoising still remains a challenge for researchers, since noise removal introduces artifacts and causes blurring in images. This paper provides different methodologies for noise reduction (or denoising) also gives us an insight about which algorithm should be used to find the most reliable and approximate estimate of the original image data given its degraded version as in [5]. Noise modeling in images is greatly affected by capturing instruments, transmission media, image quantization and discrete sources of radiation. Depending on the noise model, different algorithms can be used. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. In ultrasound image, speckle noise [1] is observed whereas in MRI images Rician noise [2] is observed.

The scope of the paper is to focus on noise removal techniques for natural images. This paper is organized as follows. In section II noise model for different types of noise is defined. Section III gives the brief idea about the evolution of image denoising research. Section IV gives the classification of various image denoising techniques. Section V gives the discussion about image denoising techniques. Finally, section VI gives the conclusions of the work.

II. NOISE MODEL

Impulse noise corruption is very common in digital images. Impulse noise is always independent and uncorrelated to the image pixels and is randomly distributed over the image. Hence unlike Gaussian noise, for an impulse noise corrupted image all the image pixels are not noisy, a number of image pixels will be noisy and the rest of pixels will be noise free. There are different types of impulse noise namely salt and pepper type of noise and random valued impulse noise. In salt and pepper type of noise the noisy pixels takes either salt value (gray level - 255) or pepper value (gray level - 0) and it appears as black and white spots on the images. If p is the total noise density then salt noise and pepper noise will have a noise density of $p/2$.This can be mathematically represented in eq. (1).

$$Yij = \begin{cases} 0 \text{ to } 255 \text{ with probability } p \\ Xij \text{ with probability } 1-p \end{cases} \qquad (1)$$

Where Yij represents the noisy image pixel, p is the total noise density of impulse noise and Xij is the uncorrupted image pixel. At times the salt noise and pepper noise may have different noise densities $p1$ and $p2$ thus the total noise density will be $p = p1 + p2$.

In case of random valued impulse noise, noise can take any gray level value from zero to 255. In this case also noise is randomly distributed over the entire image and probability of occurrence of any gray level value as noise will be same.

We can mathematically represent random valued impulse noise as in eq. (2).

$$Yij = \begin{cases} Nij \text{ with probability } p \\ Xij \text{ with probability } 1 - p \end{cases} \quad (2)$$

Where Nij is the gray level value of the noisy pixel.

The types of Noise are following:-

- Additive noise (Amplifier or Additive white Gaussian noise) in gray scale images as in eq. (3).

$$g(x, y) = f(x, y) + n(x, y) \quad (3)$$

Where g(x, y) is the result of the original image function f(x, y) corrupted by the additive Gaussian noise *n(x,* y).

- Multiplicative noise (speckle noise) in medical images as in eq. (4).

$$g(x, y) = f(x, y) * n(x, y) \quad (4)$$

Where *n(x,* y) is the multiplicative noise

- Impulse noise (Salt-and-pepper noise or bipolar fixed-valued impulse noise) in sensor images as in eq. (5).

$$g(x, y) = (1 - p)f(x, y) + p.i(x, y) \quad (5)$$

- Shot noise (Poisson noise)

III. EVOLUTION OF IMAGE DENOISING RESEARCH

Image Denoising is the fundamental problem in the field of image processing. Firstly a spatial domain approach has been adopted. One of the biggest advantages of this filter domain approach is a speed but a disadvantage is that this method was unable to preserve edges, which are identified as discontinuities in the image, On the other hand wavelet domain approach having a great advantage of preserving edges. Wavelet gives the excellent performance in image denoising due to properties such as sparsity and multiresolution structure. With the gaining popularity of Wavelet Transform in the last two decades, various algorithms have been developed for denoising in wavelet domain. The focus was shifted from the Spatial and Fourier domain to the Wavelet transform domain. Ever since Donoho's Wavelet based thresholding approach was published in 1995, there was a surge in the denoising papers being published. Although Donoho's approach 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 approach since Donoho's [4] demonstrated a simple approach to a difficult problem domain. Researchers published different ways to compute the parameters for the thresholding of wavelet coefficients. To achieve optimum threshold, data adaptive thresholds [6] were introduced Later on it was found that considerable improvements in perceptual quality could be attained by translation invariant algorithms based on thresholding of an Undecimated Wavelet Transform [7]. These thresholding techniques were applied to the non-orthogonal wavelet coefficients to reduce artifacts. Multiwavelets were also used employed to acquire similar results. Recently, much effort has been devoted to Bayesian denoising in Wavelet domain. Gaussian scale mixtures and hidden markov models have also become popular and more research is continued to be published. Tree Structures ordering the wavelet coefficients based on their magnitude, scale and spatial location have been researched. Data adaptive transforms such as Independent Component Analysis (ICA) have been explored for sparse shrinkage. Different statistical models are focused to model the statistical properties of the wavelet coefficients and its neighbors. Future trend will be towards finding more accurate probabilistic models for the non-orthogonal wavelet coefficients distribution.

IV. CLASSIFICATION OF IMAGE DENOISING TECHNIQUES

As shown in Figure 1, there are two fundamental approaches to image denoising, spatial filtering methods and transform domain filtering methods.

A. Spatial Filtering

This is the traditional method to remove noise from images where spatial filters are used. Spatial filters are further classified as linear and non-linear filters.

1) Linear filters: Linear filters also known as average filter are generally of two types: mean filter and wiener filter Linear filters too tends to destroy the edges which are sharp, destroy lines and other details of image and execute poorly in the presence of signal-dependent noise.

a) Mean Filter: Mean filter is a simple sliding window spatial filter that replaces the centre value of the window with the average values of its all nearest pixels values together with itself. Convolution mask is used to implement mean filter, which provides the outcome that is weighted sum of vales of a pixel and its neighbors. A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. The kernel is square. Often 3×3 mask is use.

b) Wiener Filter: Weiner filtering [8] process requires the information on the spectra of noise and original signal and it perform well only if the underlying signal is smooth. To overcome the weakness of spatial Domain filtering Donoho and Johnstone proposed wavelet based denoising schemes in [9,10].

2) Non-Linear Filters: Spatial filters employ a low pass filtering on groups of pixels with an assumption that noise occupies the higher frequency region of the spectrum. In Non-Linear filters, noise can be removed without identifying it exclusively. It removes the noise to very large extent but at the cost of blurring of images which in turn makes the edges in picture invisible. In the recent year's number of non-linear filters have been developed. The simplest filter is the median filter as in [11].

a) Median Filter: Median filter is one of the most important filters to remove random valued impulse noise. It comes under the category of non linear filters. In this filter the value of corrupted pixel in noisy image is replaced by median value of corresponding window. Median value is the value in the middle position of any sorted sequence as in [12]. Consider that the pixel values in neighbor-hood are taken into a sequence $x_1, x_2, x_3, \dots, x_n$ and it becomes $x_{i1} \geq x_{i2} \geq x_{i3} \dots \geq x_n$ after sorting in descending order or $x_{i1} \leq x_{i2} \leq x_{i3} \dots \leq x_n$ in ascending order.

$$x_{median} = Med\{x_i\} \tag{6}$$

$$= \begin{cases} x_{i\left(\frac{n+1}{2}\right)} & n \text{ is odd} \\ \frac{1}{2}\left[x_{i\left(\frac{n}{2}\right)} + x_{i\left(\frac{n}{2}\right)+1}\right] & n \text{ is even} \end{cases} \tag{7}$$

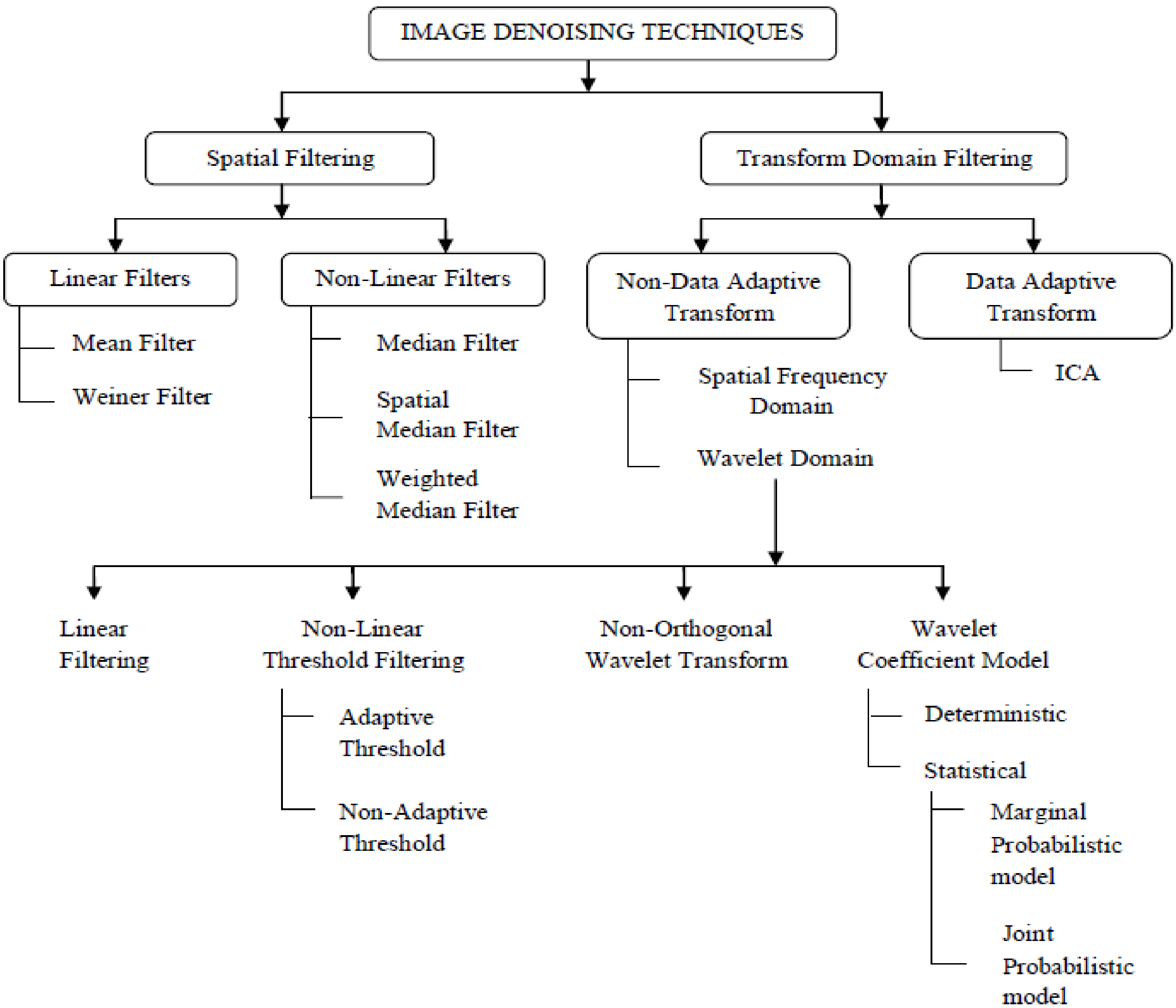

Fig.1. Classification of Image Denoising Techniques

b) Spatial Median Filter (SMF): The spatial median filter is also noise removal filter where the spatial median is calculated by calculating the spatial depth between a point and a set of point. This spatial depth is defined by eq. (8).

$$S_{depth} = 1 - \frac{1}{N-1} \left\| \sum_{i=1}^{n} \frac{X - x_i}{\|X - x_i\|} \right\| \qquad (8)$$

c) Weighted Median filter (WMF): The centre weighted median filter is an extension of the weighted median filter. The weighted median filter previously designed gives more weight to some values within the window whereas centre weighted median filter gives more weight to the central value of a window thus easier to design and implement than other weighted median filter.

B. Transform Domain Filtering

The transform domain filtering methods can be subdivided according to the basic functions. The base functions can be further classified as data adaptive and non-adaptive. Firstly, we will discuss Non-adaptive transforms because they are more popular as in [14].

1) Non-Data Adaptive Transform:

a) Spatial-Frequency Filtering: Spatial frequency domain denoising method is a kind of Transform Domain, filtering where low pass filters (LPF) is used by using Fast Fourier Transform (FFT). Here removal of noise is done by adapting a cut-off frequency and designing a frequency domain filter. But these methods are time consuming and may produce artificial frequencies in processed image.

b) Wavelet domain: In wavelet domain filtering methods are divided into linear and non-linear methods.

i) Linear Filter: Generally, Wiener filter is used in this category. Wiener filter yield optimal result in the wavelet domain. Wiener filtering is used where data corruption can be modeled as a Gaussian process and accuracy criterion is mean square error (MSE). But wiener filters results in filtered image which is visually more displeasing than original noisy image even though the filtering operation considerably reduces the MSE.

ii) Non-Linear Threshold Filtering: The most investigated domain in denoising using wavelet transform is Non-Linear threshold filtering. It basically uses the property of wavelet transform and the fact that wavelet transform maps noise in signal domain to that of noise in transform domain. Thus while signal energy becomes more concentrated into fewer coefficients in transform domain noise energy does not. The method where small coefficients are removed leaving other coefficients untouched is known as Hard Thresholding [4]. However this method generates spurious blips known as artifacts. To overcome these drawbacks Soft Thresholding was introduced where coefficients above the threshold are shrunk by the absolute value of threshold itself.

- *Non-Adaptive Threshold:* Non-Adaptive thresholds generally used are VISUShrink [9] which is completely dependent on number of data points. It suggests the best performance in terms of MSE, when the number of pixel reaches infinity. It yields the smooth images because its threshold value is quite large due to its dependency on the number of pixels in image.
- *Adaptive Threshold:* Adaptive Threshold technique involves SUREShrink [9], VISUShrink and BayesShrink methods. The Performance of SURE Shrink is better than VISUShrink because SURE Shrink uses a mixture of the universal threshold and the SURE [Stein's Unbiased Risk Estimator] threshold. When noise levels are higher than signal magnitudes the assumption that one can distinguish noise from the signal solely based on coefficient magnitudes is violated. Bayes-Shrink outperforms SURE-Shrink most of the times Bayes-Shrink minimizes the Bayes' Risk Estimator purpose assuming Generalized Gaussian prior and thus yielding data adaptive threshold. Cross Validation [19] replaces wavelet coefficient with the weighted average of neighborhood coefficient to minimize generalized cross validation (GCV) function providing optimum threshold for every coefficient.

iii) Wavelet Coefficient Model: This method utilizes the multi resolution properties of Wavelet Transform. The modeling of the wavelet coefficients can either be deterministic or statistical. This approach produces excellent output but computationally much more complex and costly as in [16].

- *Deterministic:* The Deterministic method of modeling involves forming tree structure of wavelet coefficients. Here every level in the tree representing each scale of transformation and every nodes representing wavelet coefficients.
- *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. The following two methods explain the statistical properties of the wavelet coefficients based on a probabilistic model.
  - *Marginal Probabilistic Model*: The generally used Marginal probabilistic models under this category are Gaussian mixture model (GMM) and the Generalized Gaussian distribution (GGD). GMM is simple to use but GGD is more accurate.
  - *Joint Probabilistic Model*: Here Hidden Markov Models (HMM) and Random Markov Field Models are generally used. The disadvantage of HMM is the computational burden of the training stage hence a simplified HMM was proposed.

2) Data Adaptive Transform: Independent component analysis (ICA) transformation methods recently gain more importance include key component analysis, factor analysis, and projection detection.The ICA method was successfully implemented in [17] in denoising Non-Gaussian data. ICA most extensively used method for blind source partition problem. Some applications of ICA method are seismic monitoring, reflection cancelling, machine fault detection, finding hidden factors in financial data text document analysis, audio signal processing, image processing, data mining, radio communications, time series forecasting, defect detection in patterned display surfaces, bio medical signal processing. One advantage of using ICA is it's assumption of signal to be Non-Gaussian which helps denoise images with Non-Gaussian as well as Gaussian distribution. Disadvantage of ICA based method as compared to wavelet based methods is the computational cost because it uses a sliding window and it involves sample of the same scene as in [18]. In some applications, it might be difficult to obtain the noise free training data.

V. DISCUSSION

Denoising algorithm's performance is measured using the quantitative performance measures such as signal-to-noise ratio (SNR) and peak signal-to-noise ratio (PSNR) as well as visual quality of images. Currently, Gaussian noise model can be assumed for many techniques. This may not be always true because of source of noise and nature varied sources of noise. A prior knowledge is required in ideal denoising algorithms, whereas practical procedure do not have the information. For comparing the performance with different algorithms, most of the algorithms assume variance of the noise and noise model. To test the performance of algorithm, Gaussian noise with different values is added in the natural images. Use of FFT in filtering has been restricted due to its limitations in providing sparse representation of data. Wavelet Transform is the best suited for performance because of its properties like multiresolution, multiscale nature and sparsity,. In addition to performance, issues of computational complexity must also be considered. Thresholding techniques used with the Discrete Wavelet Transform are the simplest to implement. Non-orthogonal wavelets such as UDWT and Multiwavelets improve the performance at the expense of a large overhead in their computation. HMM based methods seem to be promising but are complex.

VI. CONCLUSSION

In this paper, numerous amounts of Image Denoising Techniques are discussed and it might be possible to get confused with all the methodologies, so it is important to summarize all of those to regain the full content of the paper. The selection of Denoising technique depends on what kind of denoising is required. Further, it depends on what kind of information is required. Few examples based on literature review done in this paper. Fuzzy model will be a good choice to represent the region boundaries ambiguity. It would be a good choice if we use neural model.

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