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# A Review of Different Image Denoising Techniques

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## ABSTRACT

The purpose of image restoration is to remove the defects which degrade an image. Degradation comes in many forms such as motion blur, noise, and camera misfocus.Removing noise from the original signal is still a challenging problem for researchers. There have been several published algorithms and each approach has its assumptions, advantages, and imitations. This paper presents a review of some significant work in the area of image denoising. After a brief introduction, some popular approaches are classified into different groups and an overview of various algorithms and analysis is provided.

**Keywords: - Image, restoration, blur, noise.**

## 1. INTRODUCTION

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, and computed 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 analysed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. This paper describes different methodologies for noise reduction (or denoising) giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data given its degraded version. Noise modelling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. The scope of the paper is to focus on noise removal techniques for digital images.

## 2. IMAGE RESTORATION

Image restoration techniques aim at reversing the degradation undergone by an image to recover the true image. Image may be corrupted by degradation such as linear frequency distortion, noise, and blocking artefacts. The degradation consists of two distinct processes –the deterministic blur and the random noise. The noise may originate in the image formation process, the transmission process or a combination of them. Most restoration techniques model the degradation process and attempt to apply an inverse procedure to obtain an approximation of the original image.

## 3. CLASSIFICATION OF DENOISING ALGORITHMS

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

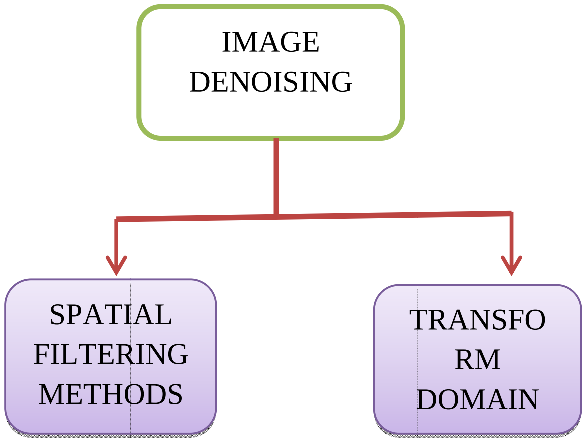


**Figure 3.1 Image denoising methods**

**3.1 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.

**I. Non-Linear Filters**

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

**II. 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 based denoising scheme in [12].

**3.2 Transform Domain Filtering**

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

**3.2.1 Spatial-Frequency Filtering**

Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods [11] the removal of the noise is achieved by designing a frequency domain filter and adapting a cut-off frequency when the noise components are decor related from the useful signal in the frequency domain. These methods are time consuming and depend on the cut-off frequency and the filter function behaviour. Furthermore, they may produce artificial frequencies in the processed image.

**3.2.2 Wavelet domain**

Filtering operations in the wavelet domain can be subdivided into linear and nonlinear methods.

**I. Linear Filters**

Linear filters such as Wiener filter in the wavelet domain yield optimal results when the signal corruption can be modelled as a Gaussian process and the accuracy criterion is the mean square error (MSE) [11]. However, designing a filter based on this assumption frequently results in a filtered image that is more visually displeasing than the original noisy signal, even though the filtering operation successfully reduces the MSE. In a wavelet-domain spatiallyadaptiveFIR Wiener filtering for image denoising is proposed where wiener filtering is performed onlywithin each scale and intrascale filtering is not allowed.

### II. Non-Linear Threshold Filtering

The most investigated domain in denoising using Wavelet Transform is the non-linear coefficientThresholding based methods. The procedure exploits scarcity property of the wavelet transform and the fact that the Wavelet Transform maps white noise in the signal domain to white noise in the transform domain. Thus, while signal energy becomes more concentrated into fewer coefficients in the transform domain, noise energy does not. It is this important principle that enables the separation of signal from noise. The procedure in which small coefficients are removedwhile others are left untouched is called Hard Thresholding [5]. But the method generates spurious blips, better known as artifacts, in the images as a result of unsuccessful attempts of removing moderately large noise coefficients.

#### a. Non-Adaptive thresholds

VISUShrink [12] 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. VISUShrink is known to yield overly smoothed images because its threshold choice can be unwarrantedly large due to its dependence on thenumber of pixels in the image.

#### b. Adaptive Thresholds

SUREShrink [12] uses a hybrid of the universal threshold and the SURE [Stein's Unbiased RiskEstimator] threshold and performs better than VISUShrink. Bayes Shrink minimizes theBayes' Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptivethreshold. BayesShrink outperforms SUREShrink most of the times. Cross Validation replaces wavelet coefficient with the weighted average of neighbourhood coefficients to minimize generalized cross validation (GCV) function providing optimum threshold for everycoefficient.

### III. Non-orthogonal Wavelet Transforms

Undecimated Wavelet Transform (UDWT) has also been used for decomposing the signal to providevisually better solution. Since UDWT is shift invariant it avoids visual artifacts such as pseudo-Gibbsphenomenon. Though the improvement in results is much higher, use of UDWT adds a large overhead of computations thus making it less feasible.

### IV. Wavelet Coefficient Model

This approach focuses on exploiting the multiresolution properties of Wavelet Transform. This technique identifies close correlation of signal at different resolutions by observing the signal across multiple resolutions. This method produces excellent output but is computationally much more complex and expensive. The modelling of the wavelet coefficients can either be deterministic or statistical.

## 4. CONCLUSION

The principle objective of image restoration is to process an image so that the result is more suitable than the original image for a specific application. In this paper, comparative study of different denoising methods for digital images performed and includesboth the methods spatial domain filters and transform domain filters to denoise image.It has been found that all noise causes degradation in the image quality which results in loss of information. The denoising of degraded image is performed using Wiener, Mean and Median filter. From review of analysis, it has been found that most of the filtering based methods are best suited for denoising.

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