Non Adaptive and Adaptive Thresholding Approach for Removal of Noise from Digital Images

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Abstract - Image denoising is a common procedure in digital image processing aiming at the removal of noise which may corrupt an image during its acquisition or transmission while sustaining its quality. 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.

I. INTRODUCTION

An image is corrupted by noise in its acquisition and transmission. The goal of image denoising is to produce good quality of the original image from noisy image. Wavelet denoising techniques remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. This paper describes different methods for noise reduction giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data.

II. CLASSIFICATION OF DENOISING TECHNIQUES

There are two basic approaches to image denoising, spatial filtering methods and transform domain filtering methods. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Spatial Low-pass filters will not only smooth away noise but also blur edges in signals and images while the high-pass filters can make edges even sharper and improve the spatial resolution but will also amplify the noisy background [2].
Fourier transform domain filters used in signal and image processing involve a trade-off between the signal-to-noise ratio (SNR) and the spatial resolution of the signal/image processed. The conventional Fast Fourier Transform (FFT) based image denoising method is essentially a low pass filtering technique in which edge is not as sharp in the reconstruction as it was in the original. The edge information is spread across frequencies because of the FFT basis functions, which are not being localized in time or space. Hence low pass-filtering results in the smearing of the edges. But, the localized nature of the wavelet transforms both in time and space results in denoising with edge preservation.

Wavelet Analysis, a new form of signal analysis is far more efficient than Fourier analysis wherever a signal is dominated by transient behavior or discontinuities. Several investigations have been made into additive noise suppression in signals and images using wavelet transforms. Much of the early work on wavelet noise removal based on thresholding the Discrete Wavelet Transform (DWT) coefficients of an image and then reconstructing it, was done by Donoho and Johnstone [3]. It has been found that wavelet based denoising is effective in that although noise is suppressed, edge features are retained without much damage [4].

2.1 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 this case, the value of an output pixel is determined by the median of the neighbourhood pixels, rather than the mean.

Advantage of median filter - Median is much less sensitive than the mean to extreme values (called outliers); therefore, median filtering is able to remove these outliers without reducing the sharpness of the image. In recent years, a variety of nonlinear median type filters such as weighted median [2], rank conditioned rank selection [3], and relaxed median [4] have been developed.

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 [5] 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 [6, 7].

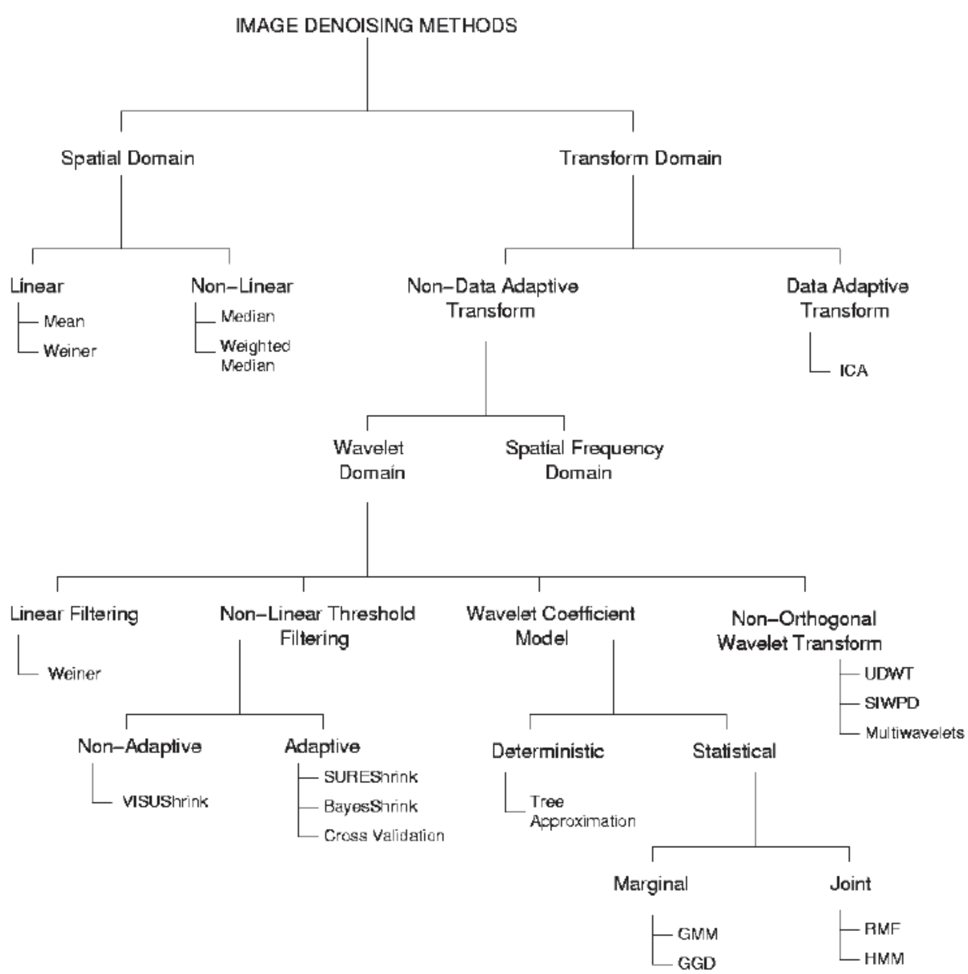

FIGURE 1 – CLASSIFICATION OF IMAGE DENOISING METHODS

2.2 Transform Domain Filtering - The transform domain filtering methods can be subdivided according to the choice of the basis functions. The basis functions can be further classified as data adaptive and non-adaptive. Non-adaptive transforms are discussed first since they are more popular. In this paper the discussion of adaptive and non-adaptive thresholding is discussed as these are the popular methods used now a days.

2.2.1 Spatial-Frequency Filtering - Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods [5] the removal of the noise is achieved by designing a frequency domain filter and adapting a cut-off frequency when the noise components are decorrelated from the useful signal in the frequency domain. These methods are time consuming and depend on the cut-off frequency and the filter function behavior. Furthermore, they may produce artificial frequencies in the processed image.

2.2.2 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 modeled as a Gaussian process and the accuracy criterion is the mean square error (MSE) [8, 9]. 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 [10] a wavelet-domain spatiallyadaptive FIR Wiener filtering for image denoising is proposed where wiener filtering is performed only within 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 coefficient thresholding based methods. The procedure exploits sparsity 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 removed while others are left untouched is called Hard Thresholding [1]. 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. To overcome the demerits of hard thresholding, wavelet transform using soft thresholding was also introduced in [1]. In this scheme, coefficients above the threshold are shrunk by the absolute value of the threshold itself. Similar to soft thresholding, other techniques of applying thresholds are semi-soft thresholding.

a. Non-Adaptive thresholds - VISUShrink [6] 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 the number of pixels in the image.

b. Adaptive Thresholds - SUREShrink [6] uses a hybrid of the universal threshold and the SURE [Stein's Unbiased Risk Estimator] threshold and performs better than VISUShrink. BayesShrink [11, 12] minimizes the Bayes' Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptive threshold. BayesShrink outperforms SUREShrink most of the times. Cross Validation [13] replaces wavelet coefficient with the weighted average of neighborhood coefficients to minimize generalized cross validation (GCV) function providing optimum threshold for every coefficient.

III. Non-orthogonal Wavelet Transforms - Undecimated Wavelet Transform (UDWT) has also been used for decomposing the signal to provide visually better solution. Since UDWT is shift invariant it avoids visual artifacts such as pseudo-Gibbs phenomenon. Though the improvement in results is much higher, use of UDWT adds a large overhead of computations thus making it less feasible. In [14] normal hard/soft thresholding was extended to Shift Invariant Discrete Wavelet Transform. In [15] Shift Invariant Wavelet Packet Decomposition (SIWPD) is exploited to obtain number of basis functions.

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 modeling of the wavelet coefficients can either be deterministic or statistical.

a. Deterministic **-** The Deterministic method of modeling involves creating tree structure of wavelet coefficients with every level in the tree representing each scale of transformation and nodes representing the wavelet coefficients. This approach is adopted in [16]. The optimal tree approximation displays a hierarchical interpretation of wavelet decomposition. Wavelet coefficients of singularities have large wavelet coefficients that persist along the branches of tree. Thus if a wavelet coefficient has strong presence at particular node then in case of it being signal, its presence should be more pronounced at its parent nodes.

b. 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. This approach has an inherent goal of perfecting the exact modeling of image data with use of Wavelet Transform. A good review of statistical properties of wavelet coefficients can be found in [17] and [18]. The following two techniques exploit the statistical properties of the wavelet coefficients based on a probabilistic model.

I. Marginal Probabilistic Model **-** In [19], authors proposed a methodology in which the wavelet coefficients are assumed to be conditionally independent zero-mean Gaussian random variables, with variances modeled as identically distributed, highly correlated random variables. An approximate Maximum A Posteriori (MAP) Probability rule is used to estimate marginal prior distribution of wavelet coefficient variances. All these methods mentioned above require a noise estimate, which may be difficult to obtain in practical applications. Simoncelli and Adelson [19] used a twoparameter generalized Laplacian distribution for the wavelet coefficients of the image, which is estimated from the noisy observations. Chang et al. [20] proposed the use of adaptive wavelet thresholding for image denoising, by modeling the wavelet coefficients as a generalized Gaussian random variable, whose parameters are estimated locally (i.e., within a given neighborhood).

II. Joint Probabilistic Model **-** The correlation between coefficients at same scale but residing in a close neighborhood are modeled by Hidden Markov Chain Model where as the correlation between coefficients across the chain is modeled by Hidden Markov Trees. Once the correlation is captured by HMM, Expectation Maximization is used to estimate the required parameters and from those, denoised signal is estimated from noisy observation using wellknown MAP estimator. A model in which each neighborhood of wavelet coefficients is described as a Gaussian scale mixture (GSM) which is a product of a Gaussian random vector, and an independent hidden random scalar multiplier.

2.2.3 Data-Adaptive Transforms **-** Recently a new method called Independent Component Analysis (ICA) has gained wide spread attention. The ICA method was successfully implemented in [21, 22] in denoising Non-Gaussian data. Drawbacks of ICA based methods as compared to wavelet based methods are the computational cost because it uses a sliding window and it requires sample of noise free data or at least two image frames of the same scene. In some applications, it might be difficult to obtain the noise free training data.

III. CONCLUSION

Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) as well as in terms of visual quality of the images. Many of the current techniques assume the noise model to be Gaussian. In reality, this assumption may not always hold true due to the varied nature and sources of noise. An ideal denoising procedure requires *a priori* knowledge of the noise, whereas a practical procedure may not have the required information about the variance of the noise or the noise model. Thus, most of the algorithms assume known variance of the noise and the noise model to compare the performance with different algorithms.

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