A First Hand Survey of Frequency Domain Denoising Algorithms and Techniques

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***Abstract-* World over, research community is facing the challenge of noise removal in multimedia viz. Images, audio, video etc. Attempts have been made, since long, to identify and remove this noise. Both, Spatial as well as Frequency domains have been thoroughly explored to devise newer and better techniques to remove these foreign bodies from the original signals. This paper is a step to carry forward the literature survey into frequency domain from the previous paper that focused on the spatial domain. It is further expected to be followed by literature survey on denoising in the Artificial Neural Network (ANN) context. The intent is to have a comprehensive survey on image denoising and use it for designing new techniques and extend existing ones to further their performance.**

***Index Terms-* BAYES Shrink, Denoising, ICA, SURE Shrink, Threshold, VISU Shrink, Wavelet.**

1.0 INTRODUCTION

The menace of contamination, that has engulfed almost everything, does not even spare images. This contamination occurs at the time of capturing the image, during communication, while being stored and worked upon. This contamination of images by unwanted signals is called Noise. Researchers everywhere are faced with a big challenge of dealing with such contaminated images. A de-contamination process has to be applied to remove the noise. This de-contamination process is called Denoising [1]. People have worked extensively on images and often newer techniques are developed and implemented to denoise images.

Various factors have to be considered while a denoising model is being worked upon viz. image capturing devices and instruments, image transmission media, quantization and digitization processes, environmental disturbances and the like. Noise that corrupts the images may be White Gaussian noise, Speckle noise, Salt & Pepper noise or any other type and knowing the type of noise sometimes plays a very vital role in the denoising process.

2.0 EVOLUTION OF THE FREQUENCY DOMAIN DENOISING TECHNIQUES

The process of denoising started with simple filtering techniques discussed previously in [2]. A plethora of algorithms and literature is devoted to this field. Later on the attention of researchers shifted from filters to frequency domain and here again, as we will see, researchers produced remarkable solutions to get better images after applying newer and newer denoising methods. Newer algorithms were devised and extended and the process still continues.

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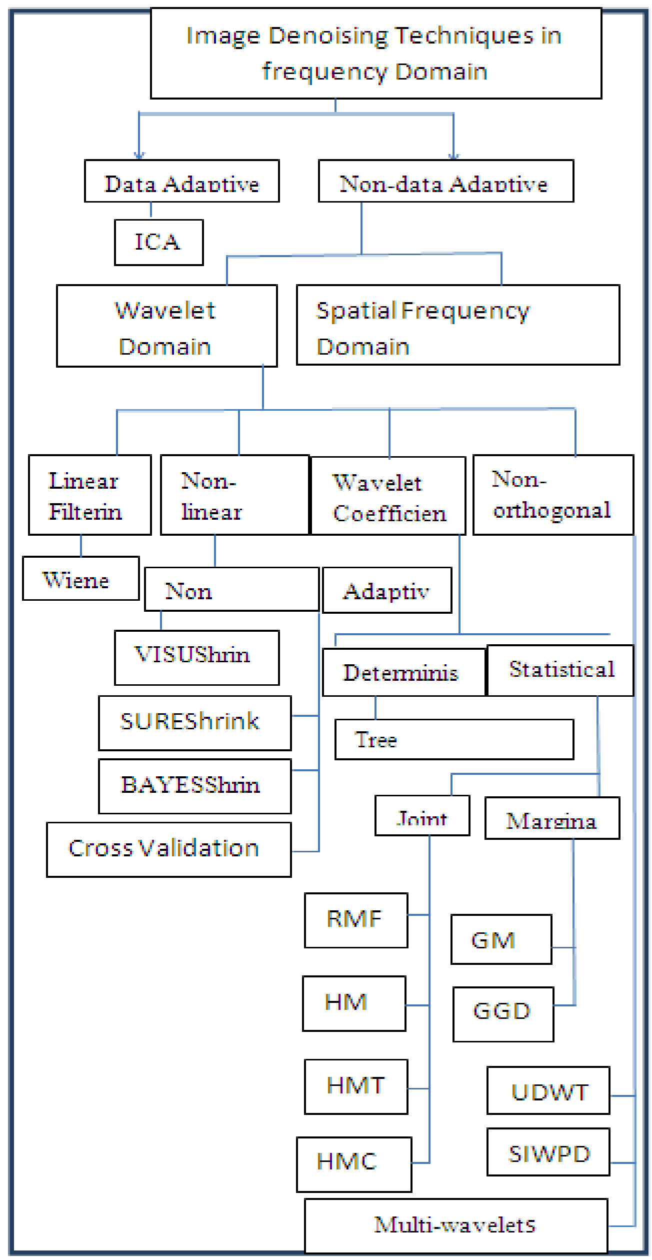

Figure 1: An outline of Image Denoising Techniques referred in the paper

3.0 DISCUSSION

Denoising in the frequency domain is broadly classified as Data-adaptive and Non-data adaptive as shown in Figure-1 above [3]. Most of the algorithms in this domain have been observed to show much better results than the algorithms in the spatial domain. Refer table-1 for results of a comparative study by the authors [4].

Table-1 (Adapted)

	PSNR			MSE			
Denoising Technique	Gaussain Noise	Salt & pepper Noise	Speckle Noise	Gaussain Noise	Salt & pepper Noise	Speckle Noise	Threshold
Mean Filter	12.5796	14.7141	20.5553	3.5902e+003	2.1962e+003	572.1996	-
Median Filter	12.3491	14.4528	20.5245	3.7859e+003	2.3324e+003	576.2773	-
Weighted Median Filter	12.5941	14.6827	20.5719	3.5783e+003	2.2121e+003	570.0253	-
Wiener Filter	14.0288	17.3274	25.5214	2.5716e+003	1.2032e+003	182.3638	-
VISU shrink	38.5863	42.1129	42.1129	9.0044	3.9976	3.9976	35.7865
SURE shrink	42.1129	42.1129	42.1129	3.9976	3.9976	3.9976	8.0000

3.1 Data Adaptive

Data adaptive transforms like Independent Component Analysis (ICA) have gained a wider acceptance and attention more recently. [5], [6] have implemented ICA successfully on non-Gaussian data. The big drawback associated with ICA is the computational cost.

3.2 Non-Data Adaptive

These transforms have been more popular for they give good results in different noise models [3].

3.2.1 Spatial Frequency Domain

In this method low Pass filters are used in Fast Fourier Transform (FFT). A cut off frequency is adopted using a frequency domain filter to filter out noise [7]. These methods consume more time as they depend on cut off frequency. They sometimes also produce artificial frequencies in the denoised images.

3.2.2 Wavelet Domain

Wavelets have shown better performance in denoising due to their sparsity, multi-resolution structure properties. Many algorithms in this domain have been introduced into the literature during past few decades.

i. Linear filters in the Wavelet Domain

Linear filters, like Weiner filter in wavelet domain give optimal results when Gaussian noise is present and MSE is used for measuring accuracy [8], [9]. Although MSE gets reduced, these filters generally produce visually more damaged images than the noisy ones. One such method has been proposed in [10]. Local adaptive filters were introduced by L. Yareslavsky [11], [12] where noisy image is analyzed in a moving window. The spectrum of the image is computed at each window position and modified, if needed.

ii. Non linear threshold filtering

Noisy coefficients in an image can be modified using certain threshold [13]. In hard thresholding coefficients smaller than a certain threshold are cancelled. This method generates artifacts in the images. To do away with this problem, soft thresholding was introduced in which coefficients larger than a certain threshold are cancelled to denoise the image [14]. Many other thresholding methods, similar to soft thresholding, like Semi soft and Garrote were also introduced later [15].

In thresholding, selecting a threshold value is a tedious job as selecting a smaller or a larger threshold many a times removes important signal/image components. Choosing an optimal threshold is based on whether the threshold is adaptive or non-adaptive to the image.

a. Adaptive Thresholds

A hybrid method of Stein's Unbiased Risk Estimator (SURE) and Universal Threshold has been discussed and used in [13]. This method is called SURE Shrink.

BAYES Shrink [16], [17] minimizes the Baye's Risk Estimation Factor. BAYES shrink performs better than SURE Shrink most of the times [3]. Another thresholding method, Cross Validation [18] replaces coefficients with weighted average of neighborhood coefficients to minimize Generalized Cross Validation (GCV) function.

b. Non Adaptive Thresholds

A nonadaptive threshold depending only on number of data points is VISU Shrink [13]. It consists of applying the soft thresholding operator using universal threshold. VISU Shrink produces a highly smoothed output image but often eliminates important image details because of selecting a large threshold [19]. LEVEL Shrink uses different thresholds for different levels of tree. LEVEL Shrink is more adaptive than VISU Shrink as it adapts to the variability from one decomposition layer to another by suing different thresholds for different levels [19].

Wavelet thresholding methods were improved by Coifman and Donoho [20] by way of averaging the estimation of all translations of degraded signal. This translation invariant Wavelet Thresholding (TIWT) considerably reduces the Gibb's effect. Stair casing, Gibb's effect and wavelet outliers are more efficiently taken care by a variation method given by S. Durand and M. Nikolova [21].

iii. Wavelet Coefficient Model

This model focuses on multi-resolution properties of wavelet transform and identifies close correlation of signal across multiple resolutions. Although computationally expensive and complex, the method gives excellent output.

a. Deterministic Wavelet Coefficient Models

Proposed in [22], this model creates a tree structure of wavelet coefficients. Each scale of transformation is represented by a level in the tree and the wavelet coefficients by every node. Donoho also proposed a deterministic model in [23] based on trees. Lu et al used a tree structure to track wavelet local maxima in scale-space [24].

b. Probabilistic/Statistical Wavelet Coefficient Models

Some properties of wavelet transform viz. Local correlation between neighborhood coefficients and multi-scale correlation between wavelets etc play interesting role in image denoising. The goal is to perfect the exact modeling of image data. [25], [26] provide a review of statistical properties of wavelet coefficients.

c. Marginal Probabilistic Models

Many homogeneous local probabilistic models have been developed to denoise images and these models have shown that marginal distribution of wavelet coefficients are highly kurtotic and often have a marked peak and heavy tails at zero. Amongst these models Gaussian Mixture Model (GMM) [17] and Generalized Gaussian Distribution (GDD) [27] are commonly used to model the distribution of wavelet coefficients. GMM has been seen to be easier to implement whereas GGD shows more accuracy. Maximum A Posteriori (MAP) probability is used to estimate marginal prior distribution of wavelet coefficient variances. A noise estimate is required in all the above methods and many people have proposed methods for such estimates, as in [16], [28].

d. Joint Probabilistic Models

For capturing inter-scale dependencies and inter-scale correlations Hidden Markovian Model (HMM) [26] and Random Markov Field (RMF) [29] are used respectively. Hidden Markovian Chain Model (HMCM) and Hidden Markov Trees (HMT) are respectively used for modeling correlation between coefficients at same scale but in a close neighborhood and correlation between coefficients across the chain.

In a model described in [30], each neighborhood of wavelet coefficients is described as a Gaussian Scale Matrix (GSM) which in turn is a product of Gaussian Random Vector and an independent hidden random scale multiplier.

Jansen and Brethel [31] have used a Markov random field for wavelet coefficients. In [26], a simple HMT, namely uHMT was proposed as a computationally simplified version of HMT.

e. Non-Orthogonal Wavelet Transform

Visual artifacts like Pseudo-Gibb's phenomenon have been dealt with Undecimated Wavelet Transform (UDWT) by way of decomposing the signal to provide better solution. The drawback with UDWT is that it is computationally complex but provides better visual results in images. The method was extended by incorporating normal thresholding in [32]. Shift Invariant Wavelet Packed Decomposition (SIWPD) is exploited in [33]. Here Basis functions are obtained to get small code length for description of the given data. Later on, Thresholding was used to denoise the data.

Multi-wavelets have also been utilized to further the performance at the cost of added complexity. These multi-wavelets are obtained by applying many mother functions to given data set. In [34], a combination of multi-wavelets and UDWT is implemented which give better results in terms of Mean Square Error.

4.0 CONCLUSION

In this paper, the authors have made an attempt to explore the denoising literature, in the frequency domain, from the vast volumes of information available for image processing. An attempt has been made to dig deep into imaging domain to get first hand information especially in the frequency domain. A classification tree has been designed and accordingly techniques of denoising have been identified. There is still a scope to dig further and explore the left out techniques and algorithms. The authors are again working on a comprehensive survey for exploring denoising literature in the context of Artificial Neural Networks. The ultimate aim of the review process is to identify gaps to design newer techniques for better image processing.

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