The procedure in which small coefficients are removed while 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. To overcome the demerits of hard thresholding, wavelet transform using soft thresholding was also introduced in [5]. 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 and Garrote thresholding [6]. Most of the wavelet shrinkage literature is based on methods for choosing the optimal threshold which can be adaptive or non-adaptive to the image. With the non-linear filter, noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on the group of pixels with the assumption that noise occupies the higher region of frequency spectrum. Generally spatial filters remove the noise to reasonable extent but at the cost of blurring the images which in turn makes the edges in the picture invisible.

G) Non-Adaptive Thresholds

It has asymptotic equivalence suggesting best performance in terms of MSE when the number of pixels reaches infinity. VISU Shrink 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.

H) Adaptive Thresholds

The assumption that one can distinguish noise from the signal solely based on coefficient magnitudes is violated when noise levels are higher than signal magnitudes. Under this high noise circumstance, the spatial configuration of neighboring wavelet coefficients can play an important role in noise-signal classifications. Signals tend to form meaningful features (e.g. straight lines, curves), while noisy coefficients often scatter randomly.

4. Non Orthogonal Wavelet Transform

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 normal hard/soft thresholding was extended to Shift Invariant Discrete Wavelet Transform. In Shift Invariant Wavelet Packet Decomposition (SIWPD) is exploited to obtain number of basis functions. Then using Minimum Description Length principle the Best Basis Function was found out which yielded smallest code length required for description of the given data. Then, thresholding was applied to denoise the data. In addition to UDWT, use of Multiwavelets is explored which further enhances the performance but further increases the computation complexity. The Multiwavelets are obtained by applying more than one mother function (scaling function) to given dataset. Multiwavelets possess properties such as short support, symmetry, and the most importantly higher order of vanishing moments. This combination of shift invariance & Multiwavelets is implemented in which give superior results for the Lena image in context of MSE.

5. Wavelet Co-Efficient Model

This approach focuses on exploiting the multi resolution 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.

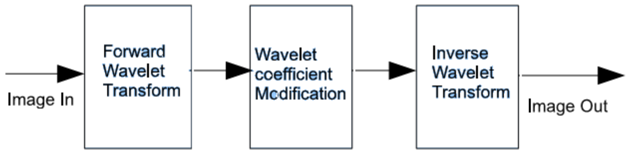

Figure 1: Noise removal using Wavelet Transform Filtering

wavelet transforms fall into transform domain filtering. Transform domain filters tend to cause Gibbs oscillations in the denoised image. Transform domain filtering can be further divided into three broad classes based on the type of transform used:

- Fourier transform filters
- Wavelet transform filters
- Miscellaneous transform filters such as curve lets, ridge lets etc. [10]

We are focusing on the wavelet transform filtering method. This method is chosen because of all the benefits associated with that. All wavelet transform noise removal algorithms involve the following three steps in general (with ref to Figure 1):

- Forward Wavelet Transform: Wavelet coefficients are obtained by applying the wavelet transform.
- Estimation: Clean coefficients are estimated from the noisy ones.
- Inverse Wavelet Transform: A clean image is obtained by applying the inverse wavelet transform.

Wavelet transform is a mathematical function that analyzes the data according to scale or resolution. Noise reduction using wavelets is performed by first decomposing the noisy image into wavelet coefficients i.e. approximation and detail coefficients. Then, by selecting a proper thresholding value the detail coefficients are modified based on the thresholding function. Finally, the reconstructed image is obtained by applying the inverse wavelet transform on modified coefficients.

Basic procedure for all thresholding method is
1. Calculate DWT if the Image.
2. Threshold the wavelet components.

3. Compute IDWT to obtain denoised estimate.

There are two thresholding functions frequently used i.e. Hard Threshold, Pan et al. [9], Soft threshold. Hard-Thresholding function keeps the input if it is larger than the threshold; otherwise, it is set to zero. Soft-thresholding function takes the argument and shrinks it toward zero by the threshold. Soft-thresholding rule is chosen over hard-thresholding, for the soft-thresholding method yields more visually pleasant images over hard thresholdding. A result may still be noisy. Large threshold alternatively, produces signal with large number of zero coefficients. This leads to a smooth signal. So much attention must be paid to select optimal threshold

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 [23]. 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. . Wavelet local maxima in scale-space, by using a tree structure. Other denoising method based on wavelet coefficient trees is proposed by Donoho [10].

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 the following two techniques exploit the statistical properties of the wavelet coefficients based on
a probabilistic model.

i. Marginal Probabilistic Model

A number of researchers have developed homogeneous local probability models for images in the wavelet domain. Specifically, the marginal distributions of wavelet coefficients are highly kurtosis, and usually have a marked peak at zero and heavy tails. The Gaussian mixture model (GMM) and the generalized Gaussian distribution (GGD) are commonly used to model the wavelet coefficients distribution[16]. Although GGD is more accurate, GMM is simpler to use. 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[17]. All these methods mentioned above require a noise estimate, which may be difficult to obtain in practical applications. Simon celli and Adel son used a two-parameter generalized Laplacian distribution for the wavelet coefficients of the image, which is estimated from the noisy observations. Chang et al. 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

This models are efficient in capturing inter-scale dependencies.. models are more efficient to capture intra scale correlations. The complexity of local structures is not well described by Random Markov Gaussian densities. Models can be used to capture higher order statistics. T h e correlation between coefficients across the chain is modeled by Trees[19]. 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 well-known MAP estimator. In a model is described 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. Here we Developed a maximum likelihood solution for estimating relevant wavelet coefficients from the noisy observations. Another approach that uses a Markov random field model for wavelet coefficients . A disadvantage of HMT is the computational burden of the training stage.

6. Data Adaptive Transforms

Recently a new method called Independent Component Analysis (ICA) has gained wide spread attention. The ICA method was successfully implemented in [8,9] in denoising Non-Gaussian data. One exceptional merit of using ICA is it's assumption of signal to be Non-Gaussian which helps to denoise images with Non-Gaussian as well as Gaussian distribution[17]. 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[22]. In some applications, it might be difficult to obtain the noise free training data.

7. Conclusions

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 de-noising 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. Gaussian Noise with different variance values is added in the natural images to test the performance of the algorithm. Not all researchers use high value of variance to test the performance of the algorithm when the noise is comparable to the signal strength.

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