# Analysis of Image Denoising Techniques

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*Abstract*— Noise is added due to data transmission reception, acquisition, process. Denoising is the first and last step to be taken before the images is used. It is necessary to apply a suitable denoising method. This paper presents a brief introduction of some image denoising methods. Potential future trends in the area of denoising are also mentioned.

## I. INTRODUCTION

Digital Image have many application such MRI images, satellite images, computer tomography, astronomy. Images collected by sensors are generally damaged by noise. Noise can be introduced by transmission, reception, compression, storage and acquisition. Images are corrupted due to noise. It is necessary to apply an appropriate denoising technique to recover for such noisy images. Image denoising is a challenging problem for researches. . Due to noise image can be blurred and some data can be lost. This paper makes introduction of some image denoising methods. Data capturing instruments data transmission by physical media data acquisition and image quantization. This paper describes different techniques for image denoising.

## II. IMAGE DENOISING RESEARCH

Image Denoising has remained a basic problem in the field of image processing. Wavelets give a capital performance in image denoising due to properties such as sparsity and multiresolution structure. Wavelet Transform gaining popularity various techniques for denoising in wavelet domain were introduced.

The focus was shifted from the Spatial and Fourier domain to the Wavelet transform domain. Wavelet based thresholding approach was published in 1995.

## III. CLASSIFICATION OF DENOISING METHODS

There are two basic methods to image denoising, spatial filtering methods and transform domain filtering methods. In spatial filtering noise is removed by processing on image itself. Where in transform domain filtering image transferred into another domain and then applied denoising technique to the image.

### A. 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.

#### 1) Non Linear Filtering

In nonlinear filtering the noise is removed without any attempts to externally identify it. Spatial filters apply a low pass filtering on groups of pixels by imagining that noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a great extent but drawback of blurring images which in turn makes the edges in pictures invisible. Solution of this nonlinear median- type filters such as weighted median, rank conditioned rank selection and relaxed median have been developed to overcome this drawback.

#### 2) Linear Filters

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. A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error .The wiener filtering method requires the information about the spectra of the noise and the original image 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 wavelet based denoising technique.

### B. Transform Domain Filtering

The transform domain filtering methods can be classified according choice of the functions. The basic functions can be further classified as data adaptive and non-adaptive. Non-adaptive transforms are discussed first.

### C. Spatial – Frequency Filtering

In frequency smoothing methods the removal of the noise is by designing a frequency domain filter. Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT). These methods are time consuming and depend on the cut-off frequency and the filter function behavior. They may produce artificial frequencies in the processed image.

### D. Wavelet Domain Filtering

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

#### 1) Linear Filters

Linear filters such as Wiener filter in the wavelet domain yield optimal results when the signal corruption can be expressed as a Gaussian process .The filtering operation successfully reduces the MSE. In a wavelet-domain spatially- adaptive FIR Wiener filtering for image denoising is proposed where wiener filtering is performed only within each scale and intrastate filtering is not allowed.

#### 2) Non Linear Filters

The most researched domain in denoising using Wavelet Transform is the non-linear coefficient thresholding based methods. The method exploits sparsity property of the wavelet transform and the fact that the Wavelet Transform converts white noise in the signal domain to white noise in the transform domain. While signal energy step-up more concentrated into fewer coefficients in the transform domain, but not for the noise. It is this important rule that enables the denoising.

The method in which small coefficients are removed while others are left untouched is called Hard Thresholding. But the procedure 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 drawback of hard thresholding, wavelet transform using soft thresholding was evaluated introduced. In this scheme, coefficients above the threshold are concentrating by the absolute value of the threshold itself. Similar to soft thresholding, other techniques of applying thresholds are semi-soft thresholding. Most of the wavelet shrinkage research is based on methods for choosing the favorable threshold which can be adaptive or non-adaptive to the image.

*a) Non-adaptive Thresholding*

VISU Shrink is non-adaptive universal threshold, which suggest only on number of data points. 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 elect can be unwarrantedly large due to its dependence on the number of pixels in the image.

*b) Adaptive Thresholding*

SURE Shrink uses a hybrid of the universal threshold and the SURE threshold and performs better than VISU Shrink. Bays' Shrink minimizes the Bays' Risk Estimator function dissonant Generalized Gaussian prior and thus yielding data adaptive threshold. Bayes Shrink outperforms SURE Shrink most of the times. Cross Validation alter wavelet coefficient with the weighted average of neighborhood coefficients to minimize generalized cross validation (GCV) function providing maximum threshold for every coefficient.

The assumption that one can classify noise from the signal purely 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 a large role in noise-signal Classifications. Signals tend to form meaningful features while noisy coefficients often scatter randomly.

*3) Non - Orthogonal Wavelet Transform*

Wavelet Transform (UDWT) has also been used for decomposing the signal to give visually better solution. Since UDWT is shift invariant it removes 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 achievable.

*4) Wavelet Coefficient Model*

This approach castrate on exploiting the multiresolution properties of Wavelet Transform. This method classifies 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.

The Deterministic method of modeling includes creating tree structure of wavelet coefficients with every level in the tree representing each scale of transformation and nodes representing the wavelet coefficients. The optimal tree approximation displays an ordered 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 certain node then in case of it being signal, its presence should be more marked at its parent nodes. If it is noisy coefficient, for instance spurious blip, then such consistent presence will be misplaced.

## IV. CONCLUSION

Many of the methods of denoising model to be Gaussian but in reality this assumption may not always true due to the varied sources of noise. Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) and mean square error (MSE).An ideal denoising procedure requires *knowledge* of the noise. First step is obtaining knowledge of noise and denoising methods then apply suitable method to noisy image which will give good result of noise free image.

## REFERENCES

[1] D. L. Donoho, "De-noising by soft-thresholding", IEEE Trans. Information Theory, vol.41, no.3, pp.613 Prentice-Hall, 1989.
[2] David L. Donoho and Iain M. Johnstone., "Adapting to unknown smoothness via wavelet shrinkage", Journal of the American Statistical Association, vol.90, no432, pp.1200-1224, December 1995. National Laboratory, July 27, 2001.
[3] Marteen Jansen, Ph. D. Thesis in "Wavelet thresholding and noise reduction" 2000.
[4] M. Lang, H. Guo, J.E. Odegard, and C.S. Burrus, "Nonlinear processing of a shift invariant DWT for noise reduction," SPIE, Mathematical Imaging, April 1995.
[5] Portilla, J., Strela, V., Wainwright, M., Simoncelli, E.P., "Image Denoising using Gaussian Scale Mixtures in the Wavelet Domain", New York University. 2002.
[6] Strela, J. Portilla , and E. P. Simoncelli, "Image denoising via a local Gaussian scale mixture model in the wavelet domain," in Proc. SPIE 45th Annual Meeting, Canada , Aug. 2000.
[7] E. P. Simoncelli and E. Adelson, "Noise removal via Bayesian wavelet coring," in Proc. IEEE International Conference on Image Processing, Switzerland, September 1996.
[8] S. G. Chang, B. Yu, and M. Vetterli, "Spatially adaptive wavelet thresholding with context modeling for image denoises," IEEE Transactions Image Processing, pp. 1522-1531, Sept. 2000.
[9] J. Romberg, H. Choi and R. G. Baraniuk, "Bayesian wavelet domain image modeling using hidden Markov models," IEEE Trans. on Image Processing, pp. 1056-1068, July 2001.
[10] M. Malfait and D. Roose, "Wavelet based image denoising using a Markov Random Field *a priori* model," IEEE Trans. on Image Processing, vol. 6, no. 4, pp. 549-565, 1997.
[11] M. Jansen and A. Bulthel, "Empirical bayes approach to improve wavelet thresholding for image noise

reduction, “American Statistical Association, vol. 96, no. 454, pp. 629-639, June 2001.

[12] Jung, "An introduction to a new data analysis tool: Independent Component Analysis", Regensburg, Oct. 2001.