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A Novel wavelet based threshold selection technique for Image Denoising

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ABSTRACT: This paper presents a wavelet threshold selection technique for noise filtering and comparison of different noise reduction techniques used in image denoising. Additive noise is applied to the image and different wavelet technique is used to remove the noise from the image. Finally all the different techniques are compared for PSNR, SSIM improvement and the processing time required.

Keywords: image denoising, wavelet transform, additive noise.

I. INTRODUCTION

Image denoising has been a well studied problem in the field of image processing. Yet researchers continue to focus attention on it to better the current state-of-the-art. Recently proposed methods take different approaches to the problem and yet their denoising performances are comparable. A pertinent question then to ask is whether there is a theoretical limit to denoising performance and more importantly, are we there yet? As camera manufacturers continue to pack increasing numbers of pixels per unit area, an increase in noise sensitivity manifests itself in the form of a noisier image. We study the performance bounds for the image denoising problem. Our work in this paper estimates a lower bound on the mean squared error of the denoised result and compares the performance of current state-of-the-art denoising methods with this bound. We show that despite the phenomenal recent progress in the quality of denoising algorithms, some room for improvement still remains for a wide class of general images, and at certain signal-to-noise levels. Therefore, image denoising has still possibilities.

II. PREVIOUS WORK

In this section we present the recent works provides us some useful information for development of the proposed work.

In this paper, Turgay Celik [1] proposes a novel technique for unsupervised change detection in multi temporal satellite images using principal component analysis (PCA) and k-means clustering. The difference image is partitioned into blocks. Ortho normal eigenvectors are extracted through PCA of $h\times h$ non overlapping block set to create an eigenvector space Simulation results show that the proposed algorithm performs quite well on combating both the zero-mean Gaussian noise and the speckle noise, which is quite attractive for change detectionin optical and SAR images.

Sudha *et al*. [2] first presents a wavelet-based thresholding scheme for noise suppression in ultrasound images. Quantitative and qualitative comparisons of the results obtained by the proposed method with the results achieved from the other speckle noise reduction techniques demonstrate its higher performance for speckle reduction. T.Ratha *et al.*[3]they described and analyzed an algorithm for cleaning speckle noise in ultrasound medical images. Mathematical Morphological operations are used in this algorithm. This algorithm is based on Morphological Image Cleaning algorithm (MIC). The algorithm uses a different technique for reconstructing the features that are lost while removing the noise. For morphological operations it also uses arbitrary structuring elements suitable for the ultrasound images which have speckle noise. Pierrick *et al.* [4] proposed a Bayesian Non Local Means-Based Speckle Filtering In their proposal, a new version of the Non Local (NL) Means filter adapted for US images is proposed. Originally developed for Gaussian noise removal, a Bayesian framework is used to adapt the NL means filter for speckle noise. Experiments were carried out on synthetic data sets with different speckle simulations. Nonlocal Means-Based Speckle Filtering for Ultrasound Images is presented by [5] In this method, an adaptation of the nonlocal (NL) means filter is proposed for speckle reduction in ultrasound (US) images. Originally developed for additive white Gaussian noise, we propose to use a Bayesian framework to derive a NL-means filter adapted to a relevant ultrasound noise model. Quantitative results on synthetic data show the performances of the proposed method compared to well-established and state-of-the-art methods. Results on real images demonstrate that the proposed method is able to preserve accurately edges and structural details of the image. M. I. H. Bhuiya *et al.* [6] presented Wavelet-Based Despeckling of Medical Ultrasound Images with The Symmetric Normal Inverse Gaussian Prior In their proposal, an efficient wavelet-based method is proposed for despeckling medical ultrasound images. A closed-form Bayesian wavelet based maximum a posteriori denoiser is developed in a homomorphic framework, based on modeling the wavelet coefficients of the log-transform of the reflectivity with a symmetric normal inverse Gaussian (SNIG) prior. A simple method is presented for obtain-ing the parameters of the SNIG prior using local neighbors. Thus, the proposed method is spatially adaptive. Rajan *et al.* [7] In their paper they discuss the speckle reduction in images with the recently proposed Wavelet Embedded Anisotropic Diffusion (WEAD) and Wavelet Embedded Complex Diffusion (WECD). Both these methods are improvements over anisotropic and complex diffusion by adding wavelet based bayes shrink in its second stage. Both WEAD and WECD produce excellent results when compared with the existing speckle reduction filters.

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III. IMAGE FILTRATION TECHNIQUES AND TRANSFORMS

A. Wavelet Transform

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing.

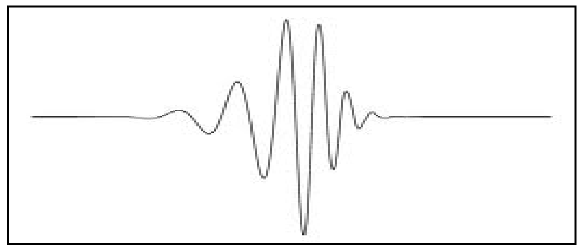

Fig. 1. Simple Wavelet.

The wavelet transform replaces the Fourier transform's sinusoidal waves by a family generated by translations and dilations of a window called a wavelet. It takes two arguments: time and scale. A discrete wavelet transform is any wavelet transform for which the wavelets are discretely sampled.

B. Wavelet Filtering

After calculating the DWT coefficient form the DWT transform the suppression or elimination of coefficients is performed there are many techniques available for the selection of coefficients and suppression of coefficients and then the inverse DWT is taken to generate the filtered image.

C. Median Filter

In signal processing, it is often desirable to be able to perform some kind of noise reduction on an image or signal. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise (but see discussion below).
The main idea of the median filter is to run through the signal entry by entry, replacing each entry with

the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal. For 1D signals, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median.

IV. PROPOSED ALGORITHM

The proposed algorithm works on wavelet thresholding and the threshold is selected by following method.

Let the sub band regions of the two-dimensional (2-D) critically sampled wavelet transform. For convenience, let us label the sub bands HH_k, HL_k, and LH_k, where k is the scale, and j is the coarsest scale. The smaller k is, the finer the scale is. Let us also define sub-band P(S). P(S) is the sub-band of the parents of the coefficients of the sub-band S. For example, if S is HH_1, then P(S) is HH_2, or if S is HL_2, then P(S) is HL_3.

To estimate the noise variance σ_n^2 from the noisy wavelet coefficients, a robust median estimator is used from the finest scale wavelet coefficients (HH_1 subband).

$$\sigma_n^2 = \text{Median}(|y_i|) / 0.6745$$

Where $\mathbf{y_i}$ is element of sub band HH_1 , $\boldsymbol{\sigma_{y1}}$ and $\boldsymbol{\sigma_{y2}}$ can be found by :

$$\hat{\sigma}_{y1}^{2} = \frac{1}{N_1^2} \sum_{y1i \in s} y_{1i}^2$$

$$\hat{\sigma}_{y2}^{2} = \frac{1}{N_2^2} \sum_{y2i \in p(s)} y_{2i}^2$$

Where σy_1 and σy_2 are Variances of y_1 and y_2 . Using these variances signal variance σ_1 & σ_2 can be estimated by applying formula given as:

$$\hat{\sigma}_1 = \sqrt{(\hat{\sigma} y_1^{2} - \hat{\sigma}_n^{2})+}$$

$$\hat{\sigma}_2 = \sqrt{(\hat{\sigma} y_2^{2} - \hat{\sigma}_n^{2})+}.$$

Using bivariate shrinkage function

$$\hat{w}_1 = \frac{(\sqrt{y_1^2 + y_2^2} - \sqrt{3}\frac{\sigma_n^2}{\sigma}) + .y_1}{\sqrt{y_1^2 + y_2^2}}$$

Each coefficient is estimated.

V. EXPERIMENTAL RESULTS

The algorithms are programmed in MATLAB and the simulated results for PSNR(Peak signal to noise ratio) and SSIM(Structural Similarity) and processing time, with different noise variance.

Table 1: Comparison of various techniques (for image distorted by noise of variance 0.05, the PSNR and SSIM of noisy image are 30.45dB and 32.15% respectively).

Method	PSNR (dB)	SSIM(%)	Time (Sec.)
LEE	32.51	62.81	5.17
Median	31.22	61.35	0.147
Adaptive	30.02	79.41	2.127
Wavelet soft	27.96	41.23	1.18
Wavelet hard	26.38	64.26	1.182

Table 2: Comparison of various techniques (for image distorted by noise of variance 0.01, the PSNR and SSIM of noisy image are 37.57dB and 63.44% respectively).

Method	PSNR (dB)	SSIM(%)	Time(Sec.)
LEE	39.35	83.93	5.19
Median	40.55	82.89	0.016
Adaptive	41.23	90.18	0.021
Wavelet soft	33.86	73.35	0.42
Wavelet hard	33.83	85.19	0.128

VI. CONCLUSION

The simulation result shows that the wavelet domain techniques take larger time than the spatial techniques and also lags the PSNR and SSIM performance (it adds the artifacts) at the lower noise levels but at higher noise level the wavelet technique outperforms them also the proposed methods will provide good PSNR value.. In Principal Component Analysis based Wavelet threshold technique, we will try to enhance performance of Peak Signal to Noise Ratio by 3-4 dB and Structure Similarity (SSIM) around 70% with lesser Processing time.

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