

Reconfigurable Wavelet Thresholding for Image Denoising while Keeping Edge Detection

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Summary

This paper proposes an reconfigurable adaptive threshold estimation method for image denoising in the wavelet domain based on the generalized Gaussian distribution (GGD) modeling of sub-band coefficients. The proposed method called Regular-Shrink is computationally more efficient and adaptive because the parameters required for estimating the threshold depend on sub-band data. Edge information is the most important high frequency information of an image, so we should try to maintain more edge information while denoising. In order to preserve image details as well as canceling image noise, we present a new image denoising method: image denoising based on edge detection. Before denoising, image's edges are first detected, and then the noised image is divided into two parts: edge part and smooth part. We can therefore set high denoising threshold to smooth part of the image and low Denoising threshold to edge part. The theoretical analyzes and experimental results presented in this paper show that, compared to commonly used wavelet threshold denoising methods, the proposed algorithm could not only keep edge information of an image, but also could improve signal-to-noise ratio of the denoised image.

Key words:

Denoising, Wavelet, Gaussain

1. Introduction

An image is often corrupted by noise in its acquisition or transmission. The goal of denoising is to remove the noise while retaining as much as possible the important signal features. Traditionally, this is achieved by linear processing such as Wiener filtering. A vast literature has emerged recently on signal denoising using nonlinear techniques, in the setting of additive white Gaussian noise. The seminal work on signal denoising via wavelet thresholding or shrinkage of Donoho and Johnstone ([1]-[3]) have shown that various wavelet thresholding schemes for denoising have near-optimal properties in the minimax sense and perform well in simulation studies of one-dimensional curve estimation. It has been shown to have better rates of convergence than linear methods for approximating functions in Besov spaces ([13], [14]). Thresholding is a nonlinear technique, yet it is very simple because it operates on one wavelet coefficient at a time.

Alternative approaches to nonlinear wavelet-based Denoising can be found in, for example, [1], [4], [8][10], [12], [18], [19], [24], [27][29], [32], [33], [35], and references therein. On a seemingly unrelated front, lossy compression has been proposed for denoising in several works [6], [5], [21], [25], [28]. Concerns regarding the compression rate were explicitly addressed. This is important because any practical coder must assume a limited resource (such as bits) at its disposal for representing the data. Other works [4], [12][16] also addressed the connection between compression and denoising, especially with nonlinear algorithms such as wavelet thresholding in a mathematical framework. However, these latter works were not concerned with quantization and bitrates: compression results from a reduced number of nonzero wavelet coefficients, and not from an explicit design of a coder. The intuition behind using lossy compression for Denoising may be explained as follows. A signal typically has structural correlations that a good coder can exploit to yield a concise representation. White noise, however, does not have structural redundancies and thus is not easily compressible. Hence, a good compression method can provide a suitable model for distinguishing between signal and noise. The discussion will be restricted to wavelet-based coders, though these insights can be extended to other transform-domain coders as well. A concrete connection between lossy compression and Denoising can easily be seen when one examines the similarity between thresholding and quantization, the latter of which is a necessary step in a practical lossy coder. That is, the quantization of wavelet coefficients with a zero-zone is an approximation to the thresholding function. Thus, provided that the quantization outside of the zero-zone does not introduce significant distortion, it follows that wavelet-based lossy compression achieves denoising. With this connection in mind, this paper is about wavelet thresholding for image denoising and also for lossy compression. The threshold choice aids the lossy coder to choose its zero-zone, and the resulting coder achieves simultaneous denoising and compression if such property is desired.

The paper is organized as follows. Section 2 introduces the concept of wavelet thresholding. Section 3 explains the parameter estimation for Regular-Shrink. Section 4 describes the proposed denoising algorithm. Experimental results & discussions are given in section 5 for four test images at various noise levels. Finally the conclusions are made in section 6.

2. Wavelet Transform

Discrete Wavelet transform (DWT) represents an image in terms of wavelets which are called energy packets and of course they are as a sum of wavelet functions with different locations and scales by any factor [17]. Any kind of decomposition of an image into wavelets involves a pair of waveforms: one to represent the high frequencies corresponding to the detailed parts of an image (wavelet function) and one for the low frequencies or smooth parts of an image (scaling function). Fig. 1 shows two waveforms of a family discovered in the late 1980s by Daubechies: the right one can be used to represent detailed parts of the image and the left one to represent smooth parts of the image. The two waveforms are translated and scaled on the time axis to produce a set of wavelet functions at different locations and on different scales. Each wavelet contains the same number of cycles, such that, as the frequency reduces, the wavelet gets longer. High frequencies are transformed with short functions (low scale). Low frequencies are transformed with long functions (high scale). During computation, the analyzing wavelet is shifted over the full domain of the analyzed function. The result of WT is a set of wavelet coefficients, which measure the contribution of the wavelets at these locations and scales.

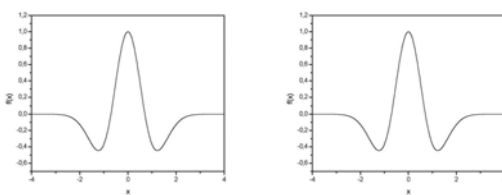


Fig1: A typical Wavelet Transform

3. Wavelet Thresholding

Let $f=f_{ij} \quad j = 1; 2:::M$ denote the $M \times M$ matrix of the original image to be recovered and M is some integer power of 2. During transmission the signal f is corrupted by independent and identically distributed (i.i.d) zero

mean, white Gaussian Noise n_{ij} with standard deviation σ i.e. $n_{ij} \sim N(0; \sigma^2)$ and at the receiver end, the noisy observations is obtained. The goal is to estimate the signal f from noisy observations g_{ij} such that Mean Squared error (MSE)[11] is minimum. Let W and W^{-1} denote the two dimensional orthogonal discrete wavelet transform (DWT) matrix and its inverse respectively. Then $Y = Wg$ represents the matrix of wavelet coefficients of g having four subbands (LL, LH, HL and HH) [7], [11]. The subbands HHk, HLk, LHk are called details, where k is the scale varying from 1, 2, J and J is the total number of decompositions. The size of the subband at scale k is $N/2^k$. The subband LLJ is the low-resolution residue. The wavelet thresholding denoising method processes each coefficient of Y from the detail subbands with a soft threshold function to obtain X . The denoised estimate is inverse transformed to $f = W^{-1}X$. In the experiments, soft thresholding has been used over hard thresholding because it gives more visually pleasant images as compared to hard thresholding; reason being the latter is discontinuous and yields abrupt artifacts in the recovered images especially when the noise energy is significant.

4. Estimation of the parameter of Regular Shrink

This section describes the method for computing the various parameters used to calculate the threshold value (TN), which is adaptive to different subband characteristics.

$$T_N = \frac{\beta \sigma^3}{\sigma_y} \tag{1}$$

Where, the scale parameter β is computed once for each scale using the following equation:

$$\beta = \sqrt{\log \frac{L_k}{J}} \tag{2}$$

where $\sigma = \frac{\text{median}(Y_{ij})}{0.7651}$ σ is noise standard deviation,

which is estimated from the subband HH1, using the formula [7][13].

4. Image Denoising Algorithm

This section describes the proposed image denoising algorithm, which is reconfigurable and also keeps edge detection that achieves near optimal soft thresholding in the wavelet domain for recovering original image from the noisy one. The algorithm is simple to implement and computationally very efficient. It has following steps

1. Conduct 2-D scale decomposition [11] of the image corrupted by Gaussian noise using wavelet transform but the edges of the image must not be corrupted.
2. Calculate the noise variance m_2 for each level of matrix which can be obtained using performance basis of the image that is used in the test bench using equation (3).
3. For each level, compute the scale parameter using equation (2) and also calculate that the noise variance should be less than that of the Gaussian one.
4. For each subband which can also include the high pass residual noise components
 - a. Compute the standard deviation
 - b. Compute threshold peaks using equation (1).
 - c. Apply soft thresholding or baseshrink to the noisy coefficients.
5. Invert the 2D scale decomposition to reconstruct the denoised image

5. Experiment Results

The simulations have been performed on various natural gray scale test images like House, Tree, Lena, and Barbara of size 256 X 256 at different noise levels =10, 25, 35, 55. The reconfigurable wavelet that has been used here is Daubechies because of its least asymmetric compactly supported wavelet with eight vanishing moments [14]. To assess the performance of Wavelet, it is compared with SureShrink, BayesShrink, OracleThresh and Wiener algorithm [14, 18, 22, and 31]. To benchmark against the best possible performance of a multi-threshold estimate, while keeping the edge detection, the comparison include OracleShrink, which is treated as the best soft thresholding algorithm which exists in the literature. The PSNR from various methods are compared in Table I and the data are collected from an average of five runs. With no explanation the Regular-Shrink outperforms SureShrink and BayesShrink, also it is also observed that most of the time in terms of PSNR as well as in terms of visual quality. Moreover Regular-Shrink is 22% faster than BayesShrink. The choice of soft thresholding over median thresholding and hard thresholding is justified from the results of best possible performance of a hard threshold estimator, with respect to reconfigurable wavelet approximations should be done OracleThresh. Comparisons are made with the best possible techniques, which exists in the literature. The results in the table I show that PSNR are considerably worse than the nonlinear thresholding methods, especially when is large. The image quality is also not as good as those of the thresholding methods. Fig. 1 shows the noisy image and resulting images of Preposed Algorithm, Wiener filter, BayesShrink and Regular-Shrink for Lena at = 30.



Figure 2: Resolution (256 X 256): Lena (Left top), Proposed Algorithm of Lena (Right Top), Sureshrink (left Bottom), BayesShrink (Left bottom)

Table 1: Simulation Results which show that proposed algorithm is better than other algorithms

	SureShrink	Bayes Shrink	Wiener	Proposed Algorithm
Lena				
$\sigma =10$	33.1908	33.8998	31.6810	34.9011
$\sigma =20$	31.9810	29.9879	29.1657	32.6733
$\sigma =30$	28.9091	25.2342	26.4161	30.8979
$\sigma =40$	26.1087	23.5721	21.8768	27.7682
House				
$\sigma =10$	38.7282	39.1018	36.9303	39.3030
$\sigma =20$	35.1910	37.1819	33.1203	36.1203
$\sigma =30$	33.8719	34.8393	30.1910	34.1910
$\sigma =40$	31.8191	32.1292	31.9101	33.9101
Barbara				
$\sigma =10$	36.9190	35.8023	38.0981	40.9823
$\sigma =20$	34.9101	33.8098	37.0939	38.2983
$\sigma =30$	33.1011	31.9818	35.9422	36.9822
$\sigma =40$	32.0101	29.0101	31.0982	34.9222

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