



A Better Thresholding Technique For Image Denoising Based On Wavelet Transform

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ABSTRACT: Wavelet transforms enable us to represent signals with a high degree of scarcity. Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. The aim of this project was to study various thresholding techniques such as SureShrink, VisuShrink and BayesShrink and determine the best one for image denoising.

KEYWORDS: Wavelet, Thresholding, Denoising, SureShrink, VisuShrink and BayesShrink.

I. INTRODUCTION

In many applications, image denoising is used to produce good estimates of the original image from noisy observations. The restored image should contain less noise than the observations while still keep sharp transitions (i.e. edges). Wavelet transform, due to its excellent localization property, has rapidly become an indispensable signal and image processing tool for a variety of applications, including compression and denoising. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content. It involves three steps: a linear forward wavelet transform, nonlinear thresholding step and a linear inverse wavelet transform.

II. RELATED WORK

Wavelet thresholding first proposed by Donoho is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. It removes noise by killing coefficients that are insignificant relative to some threshold, and turns out to be simple and effective, depends heavily on the choice of a thresholding parameter and the choice of this threshold determines, to a great extent the efficacy of denoising.

Researchers have developed various techniques for choosing denoising parameters and so far there is no “best” universal threshold determination technique.

The aim of this project was to study various thresholding techniques such as SureShrink, VisuShrink and BayesShrink and determine the best one for image denoising.

III. THRESHOLDING

A. Introduction:

The plot of wavelet coefficients in Fig 1 suggests that small coefficients are dominated by noise, while coefficients with a large absolute value carry more signal information than noise. Replacing noisy coefficients (small coefficients below a certain threshold value) by zero and an inverse wavelet transform may lead to a reconstruction that has lesser noise.

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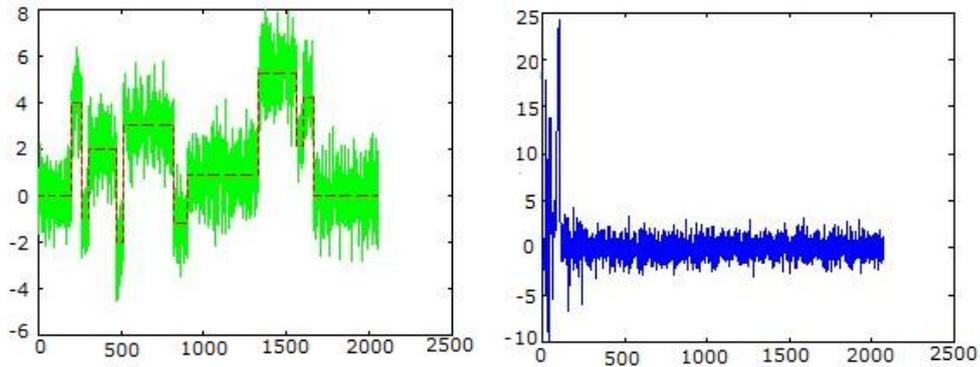


Figure 1: A Noisy Signal in Time domain and Wavelet Domain. Note the scarcity of coefficients

B. Hard and Soft Thresholding :

Hard and soft thresholding with threshold λ , are defined as follows: The hard thresholding operator is defined as: $D(U, \lambda) = U$ for all $|U| > \lambda = 0$ otherwise u the soft thresholding operator on the other hand is defined as: $D(U, \lambda) = \text{sgn}(U)\max(0, |U| - \lambda)$

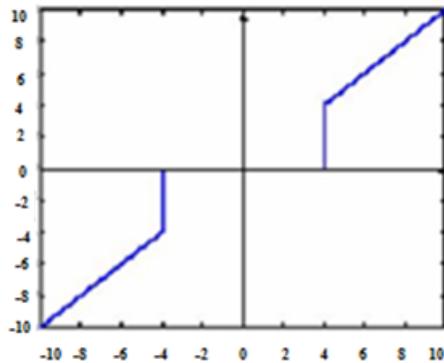


Figure 2: Hard Thresholding

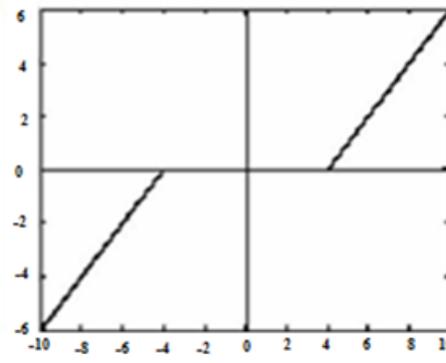


Figure 3: Soft Thresholding

Blocks

	Hard	Soft
Haar	1.2	1.6
Db2	1.2	1.6
Db4	1.2	1.6
Db8	1.2	1.8

Bumps

	Hard	Soft
Haar	1.2	1.6
Db2	1.2	1.6
Db4	1.2	1.6
Db8	1.2	1.8

HeavySine

	Hard	Soft
Haar	1.4	1.6
Db2	1.4	1.6
Db4	1.4	1.6
Db8	1.4	1.6

Doppler

	Hard	Soft
Haar	1.6	2.2
Db2	1.6	1.6
Db4	1.6	2.0
Db8	1.6	2.2

Table1: Best Thresholds empirically found with different denoising schemes, in terms of MSE

C. Comparison with Universal Threshold :

The threshold $\lambda_{UNIV} = \sqrt{2 \ln N \sigma}$ (N being the signal length, σ^2 being the noise variance) is well known in wavelet literature as the Universal threshold. It is the optimal threshold in the asymptotic sense and minimizes the cost function of the difference between the function and the soft threshold version of the same in the L2 norm sense (i.e. it minimizes $E\|Y_{\text{Thresh}} - Y_{\text{Orig}}\|^2$). In our case, $N = 2048$, $\sigma = 1$ therefore theoretically $\lambda_{UNIV} = \sqrt{(2 \ln (2048)(1))} = 3.905$. As seen from the table, the best empirical thresholds for both hard and soft thresholding are much lower than this value, independent

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of the wavelet used. It therefore seems that the universal threshold is not useful to determine a threshold. However, it is useful for obtain a starting value when nothing is known of the signal condition. One can surmise that the universal threshold may give a better estimate for the soft threshold if the number of samples is larger (since the threshold is optimal in the asymptotic sense).

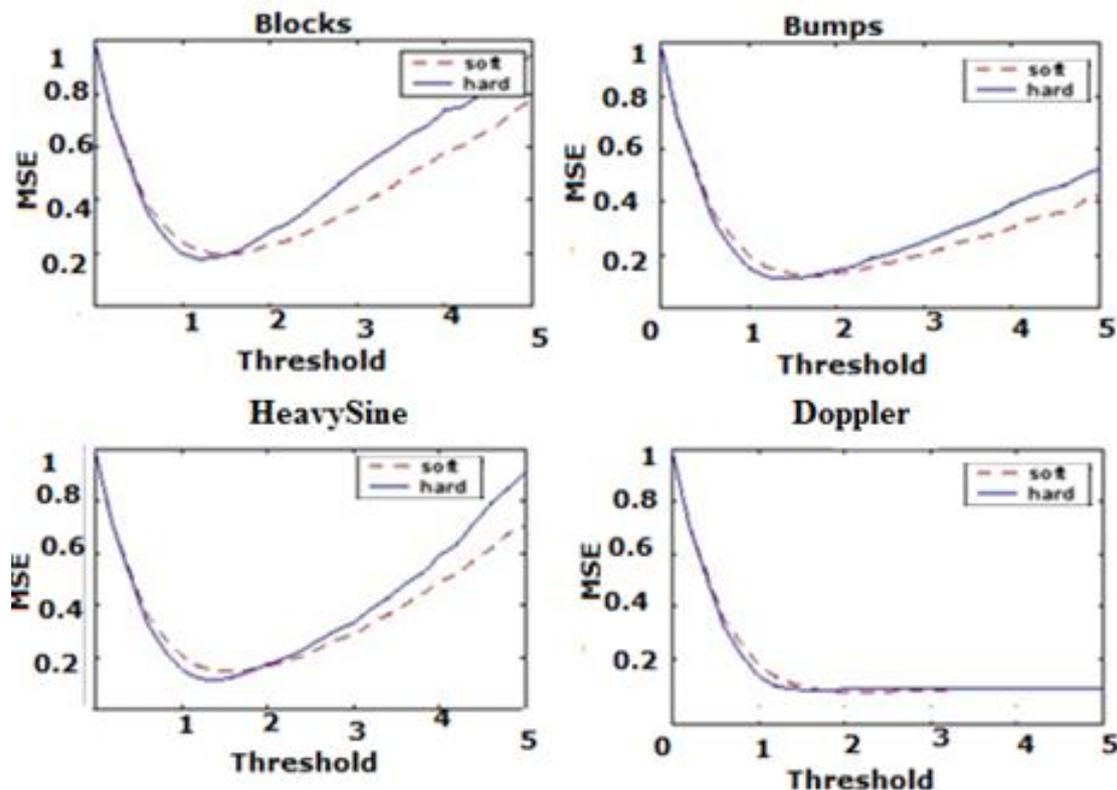


Figure 4: MSE v/s Threshold values for the four test signals

IV. IMAGE DENOISING USING THRESHOLDING

The problem boils down to finding an optimal threshold such that the mean squared error between the signal and its estimate is minimized. The wavelet decomposition of an image is done as follows: In the first level of decomposition, the image is split into 4 sub bands, namely the HH, HL, LH and LL sub bands. The HH subband gives the diagonal details of the image; the HL subband gives the horizontal features while the LH subband represents the vertical structures. The LL subband is the low resolution residual consisting of low frequency components and it is this subband which is further split at higher levels of decomposition. The different methods for denoising we investigate differ only in the selection of the threshold.

The basic procedure remains the same:

1. Calculate the DWT of the image.
2. Threshold the wavelet coefficients(Threshold may be universal or subband adaptive)
3. Compute the IDWT to get the denoised estimate

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Figure 5: 2D DWT

Soft thresholding is used for all the algorithms due to the following reasons: Soft thresholding has been shown to achieve near minimax rate over a large number of Besov spaces. Moreover, it is also found to yield visually more pleasing images. Hard thresholding is found to introduce artifacts in the recovered images.

Global Thresholding: Threshold Selection by Universal Thresholding:

Universal Threshold:

Original Image	Noisy Image
	
Denoised Image using Haar at level 1 obtained by wavelet coefficient thresholding using global positive HARD threshold	Denoised Image using Haar at level 1 obtained by wavelet coefficient thresholding using global positive SOFT threshold
	

Figure 6.1

Original Image	Noisy image
	
Denoised Image using Db 5 at level 1 obtained by wavelet coefficients thresholding using global positive Hard threshold	Denoised Image using Db 5 at level 1 obtained by wavelet coefficients thresholding using global positive Soft threshold
	

Figure 6.2

We now study three thresholding techniques: VisuShrink, SureShrink and BayesShrink and investigate their performance for denoising on a picture.

A. *VisuShrink*:

VisuShrink is thresholding by applying the Universal threshold proposed by Donoho and Johnstone. This threshold is given by $\sigma\sqrt{2 \log M}$ where σ is the noise variance and M is the number of pixels in the image. It is proved in that the maximum of any M values iid as $N(0, \sigma^2)$ will be smaller than the universal threshold with high probability, with the probability approaching 1 as M increases. Thus, with high probability, a pure noise signal is estimated as being identically zero. However, for denoising images, VisuShrink is found to yield an overly smoothed estimate as seen in Figure 7.1-7.4. This is because the Universal Threshold (UT) is derived under the constraint that with high probability, the estimate should be at least as smooth as the signal. So the UT tends to be high for large values of M , killing many signal coefficients along with the noise. Thus, the threshold does not adapt well to discontinuities in the signal.

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Global Thresholding: Threshold Selection by VisuShrink:

VisuShrink:

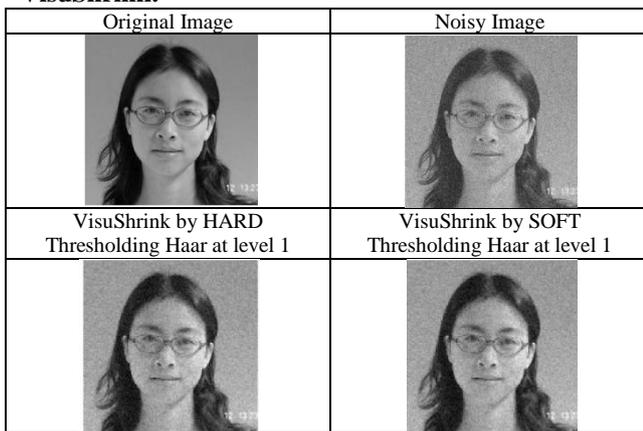


Figure 7.1

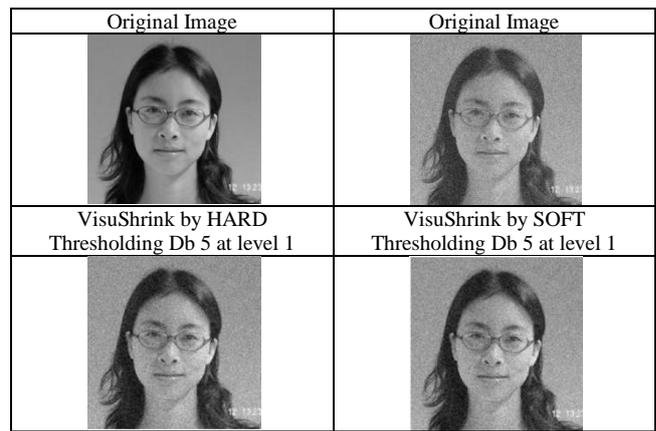


Figure 7.2

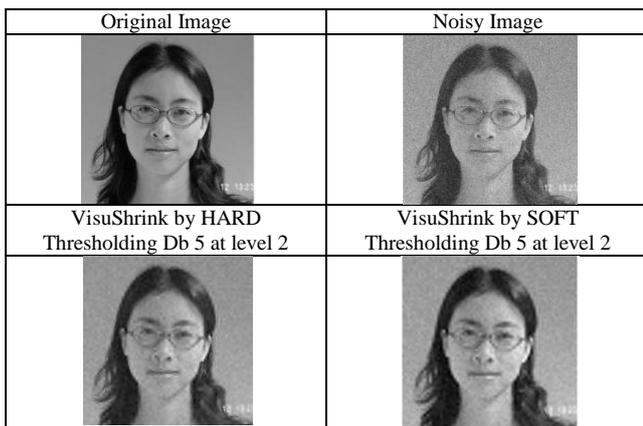


Figure 7.3

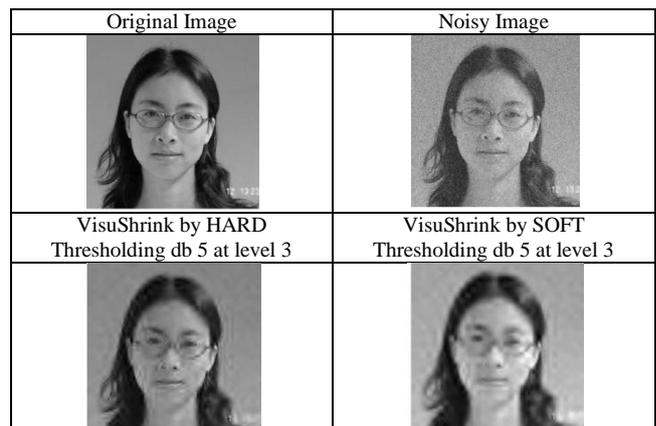


Figure 7.4

B. SureShrink:

SureShrink is a thresholding by applying subband adaptive threshold, a separate threshold is computed for each detail subband based upon SURE (Stein's Unbiased estimator for Risk), a method for estimating the loss $\| \hat{\mu} - \mu \|^2$ in an unbiased fashion. In our case let wavelet coefficients in the j th subband be $\{X_i: i=1, \dots, d\}$, $\hat{\mu}$ is the soft threshold estimator $\hat{X}_t = \eta_t(X_i)$ we apply Stein's result [1] to get an unbiased estimate of the risk $E\| \hat{\mu}^{(t)}(x) - \mu \|^2$:

$$SURE(t; X) = d - 2 \sum_{i: |X_i| \leq t} |X_i| + \sum_{i=1}^d \min(|X_i|, t)^2$$

For an observed vector x (in our problem, x is the set of noisy wavelet coefficients in a Subband, we could find the threshold t^s that minimizes $SURE(t, X)$, $t^s = \arg \min SURE(t, X)$

The results obtained for the image on my picture using SureShrink are shown in Figure 8.1-8.5. The 'Db5' wavelet coefficient was used with 4 levels decomposition. Clearly, the results are much better than VisuShrink. The sharp features of image are retained and the MSE is considerably lower. This because SureShrink is subband adaptive.

C. BayesShrink:

BayesShrink is an adaptive data-driven threshold for image denoising via wavelet soft-thresholding. The threshold is driven in a Bayesian framework, and we assume generalized Gaussian distribution (GGD) for the wavelet coefficients in each detail subband and try to find the threshold T which minimizes the Bayesian Risk. The results obtained by

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BayesShrink for my own picture is shown in Figure 9.1-9.5. The 'Db5' wavelet was used with four levels decomposition. We found that BayesShrink performs better than SureShrink in terms of MSE. The reconstruction using BayesShrink is smoother and more visually appealing than one obtained using SureShrink

Adaptive Thresholding: Threshold Selection by BayesShrink & SureShrink:

BayesShrink & SureShrink:

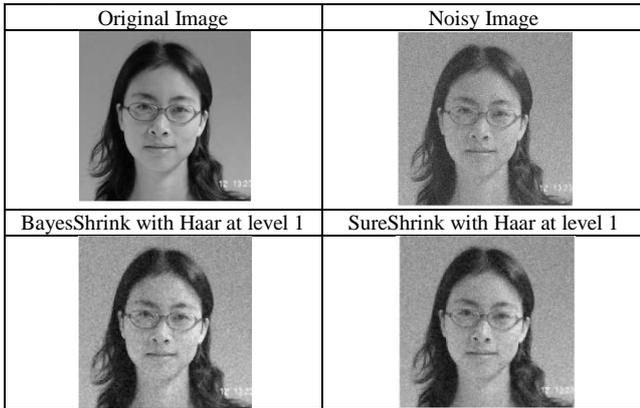


Figure 8.1 & Figure 9.1

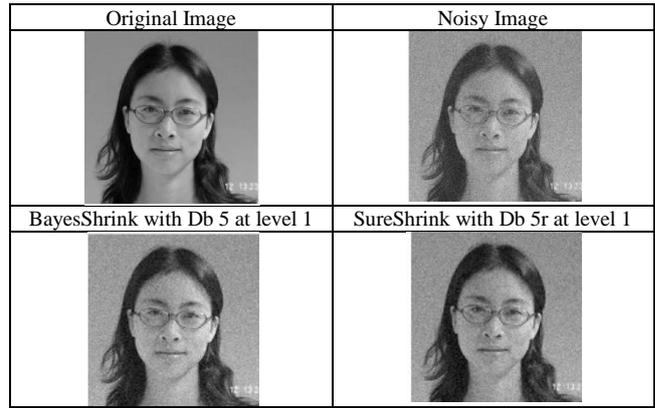


Figure 8.2 & Figure 9.2

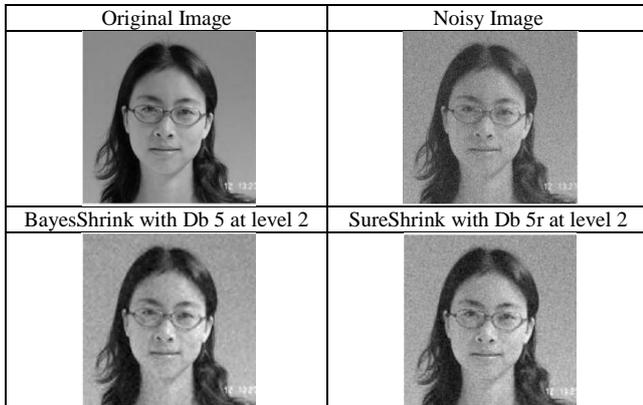


Figure 8.3 & Figure 9.3

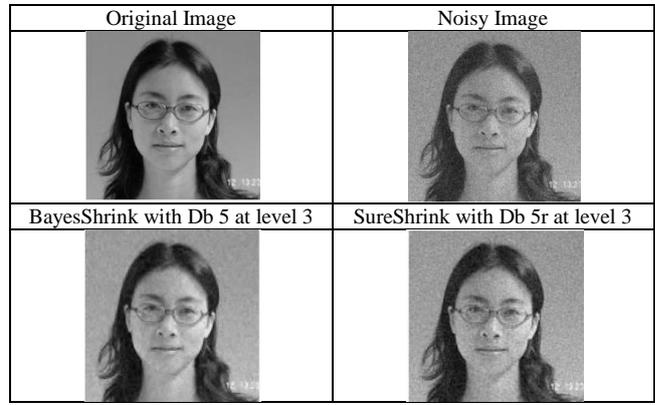


Figure 8.4 & Figure 9.4

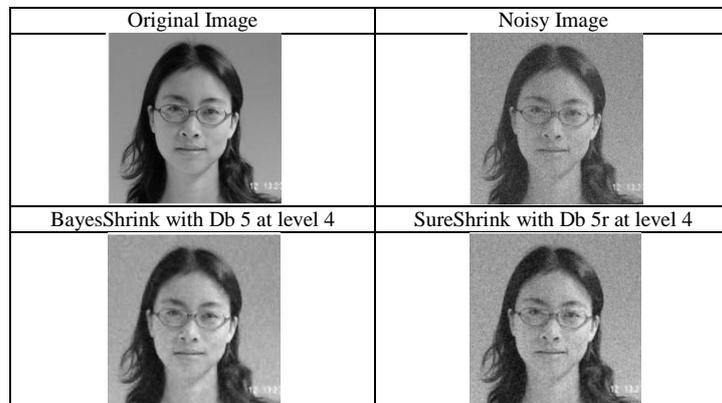


Figure 8.5 & Figure 9.5

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V. EXPERIMENTAL RESULTS

Following are the results of running the denoising algorithms for the methods discussed above on my picture. The denoising is done after adding the Gaussian noise with standard deviation 18 and mean 0 in the original picture. The MSE is calculated and compared for all the methods (see Figure 10). The results are provided as a bar chart in the end as well they are tabulated. The figures and MSE are compared for the global and adaptive thresholding techniques. The results are provided for thresholds selected by VisuShrink hard and soft methods and thresholds selected by default universal threshold for hard and soft thresholding. Similar thing is done with the BayesShrink and SureShrink methods.

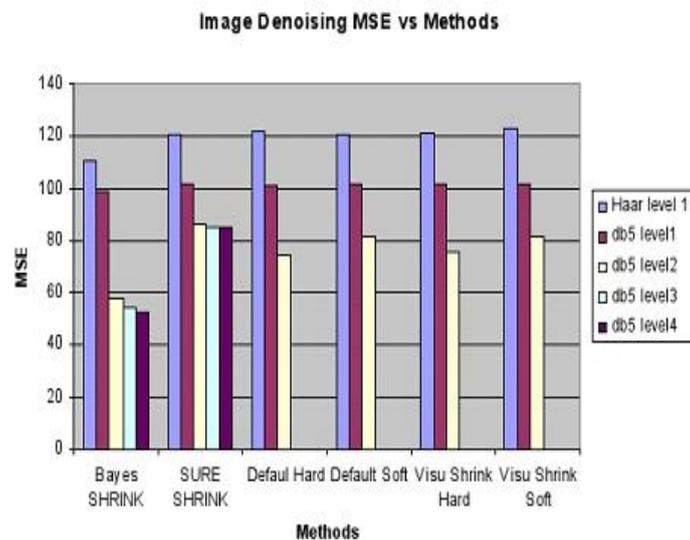


Figure 10: Comparison between all the models based on MSE

VI. CONCLUSION AND FUTURE WORK

We have seen that wavelet thresholding is an effective method of denoising noisy signals. We first tested hard and soft on noisy versions of the standard 1-D signals and found the best threshold. We then investigated many soft thresholding schemes such as VisuShrink, SureShrink and BayesShrink for denoising images. We found that subband adaptive thresholding performs better than a universal thresholding. Among these, BayesShrink gave the best results. This validates the assumption that the GGD is a very good model for the wavelet coefficient distribution in a subband. An important point to note is that although SureShrink performed worse than BayesShrink, it adapts well to sharp discontinuities in the signal. This was not evident in the natural images we used for testing. It would be instructive to compare the performance of these algorithms on artificial images with discontinuities (such as medical images). It would be interesting to try denoising (and Compression) using other special cases of the GGD such as the Laplacian (GGD with $\beta = 1$). Most images can be described with a GGD with shape parameter β ranging from 0.5 to 1. So a Laplacian prior may give better results than a Gaussian prior ($\beta = 2$) although it may not be as easy to work with.

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BIOGRAPHY



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