Denoising Techniques for Digital Modulated Signals and an Overview

[1]Sudipta Nag, [2]Jaspal Bagga.
[1]M.E.Scholar, [2]Professor
SSCET(SSTC), Bhilai(C.G.),India

***Abstract* - Denoising is a process of reduction of noise from signals. There are various techniques of denoising methods for one dimensional signals. Our motivation of this paper is to study and highlight the approaches which has been discussed and analyzed earlier. Based on the study some better methodology with the loop area is suggested where some method for better noise reduction can be applied. A thresholding Blackman windowed Gabor transforms, a robust wavelet-based estimator using a robust loss Function are compared with Gauss-windowed Gabor threshold denoising and wavelet-based denoising, and is found to be superior in most cases.**

***Index Terms* - Signals, Denoising, Thresholding Blackman windowed Gabor transforms, Wavelet-based denoising.**

I. INTRODUCTION

In real world, signals do not exist without noise, which may be negligible (i.e. high SNR) under certain conditions. The process of noise reduction is referred to as signal denoising or simply denoising. The noise adds high-frequency components to the original signal which is smooth, a characteristic effect of noise. During transmission, processing and reception, these signals get corrupted by noise. Therefore, it has been very necessary to device an effective method to remove these unwanted noises from these signals of importance. For this purpose various signal de-noising techniques such as linear methods (Fourier transform de-noising, Wiener filtering) and non-linear methods (wavelet transform de-noising) have been proposed by the researchers. Linear methods of signal de-noising have been widely used for noise removing up to 1990, because of their relative simplicity. However, since these methods are based upon the assumption that the signals are stationary, their effectiveness is generally acceptable but limited. But in reality, real-world signals have typically non-stationary statistical characteristics. Therefore, nonlinear methods like wavelet transform, thresholding Blackman windowed Gabor transforms, Gauss-windowed Gabor threshold denoising have been an active area of research for last two decades because of their ability to elucidate, simultaneously, the spectral and temporal information in a signal [1].The performance of the proposed method is evaluated by computing the signal-to-noise ratio (SNR) and the root-mean-square error (RMSE) after denoising. Results reveal that the proposed method offers superior performance than the traditional methods no matter whether the signals have heavy or light noises embedded.[2]

There is a wide range of applications where denoising is important. Examples are medical signal analysis, data mining, radio astronomy etc. Each application has its special requirements, like noise removal in medical signals requires special care, involves smoothing of the noisy signal (e.g., using low-pass filter) may cause the loss of details. There are many approaches in the literature for the task of denoising, roughly divided into two categories: denoising in the original signal domain (e.g., time or space) and denoising in the transform domain (e.g., Fourier or wavelet transform).[3]

In [4], wavelet transform is used for denoising techniques. The hard and soft thresholding are used, but there is a main drawback i.e. around discontinuities it creates Gibbs phenomenon. Here, traditional method of total variation minimization is used for denoising.

Due to simple calculation and good denoising effect, in [5] wavelet threshold denoising method has been discussed. Here, threshold is an important parameter that affects the denoising effect. To improve the denoising, a new threshold considering interscale correlation is presented. Another signal denoising method based on the classical three step procedure analysis-threshold-synthesis and the Spectral Intrinsic Decomposition (SID) in [6]. This method consists of an iterative thresholding of the SID components. The SID-based removal method reduces noise and can retain useful discontinuities of the signal as effectively as the wavelet techniques based on soft thresholding.Also, using discrete wavelet transforms using different wavelet bases (Daubechies and Symlets) [7], reduce the background noise in speech signals. In [8], a time-domain method for smoothing and reducing the noise level in LiDAR data, where Singular Value Decomposition (SVD) based Savitzky-Golay (S-G) approach is used.

The remainder of this paper is organized as follows: Section 2 summarizes the basic theory of some denoising techniques. Finally, conclusions are given in Section 3.

II. DENOISING TECHNIQUES

A thresholding Blackman windowed Gabor transforms : A Gabor transform of f, with window function w, is defined as follows. First, multiply $\{f(t_k)\}$ by a sequence of shifted window functions $\{w(t_k - \tau_m)\}$, producing a sequence of time localized subsignals,$\{f(t_k)w(t_k - \tau_m)\}_{m=1}^{M}$. Uniformly spaced time values $\{\tau_m\}_{m=1}^{M}$ are used for the shifts. The windows $\{w(t_k - \tau_m)\}$

are all compactly supported and overlap each other. Second, because w is compactly supported one treated each subsignal $\{f(t_k)w(t_k - \tau_m)\}$ as a finite sequence and apply an N-point FFT $\mathcal{F}$ to it. This yields the Gabor transform of $\{f(t_k)\}$:

$$\{\mathcal{F}\{f(t_k)\,w(t_k - \tau_m)\}_{m=1}^{M}. \qquad [13]$$

Here, proposed method Hard Gabor (Blackman), compared with three other methods:
Hard Gabor (Gauss) and two wavelet based methods Sure Shrink and Bayes Shrink. One compared MSEs for test signals using data for Hard

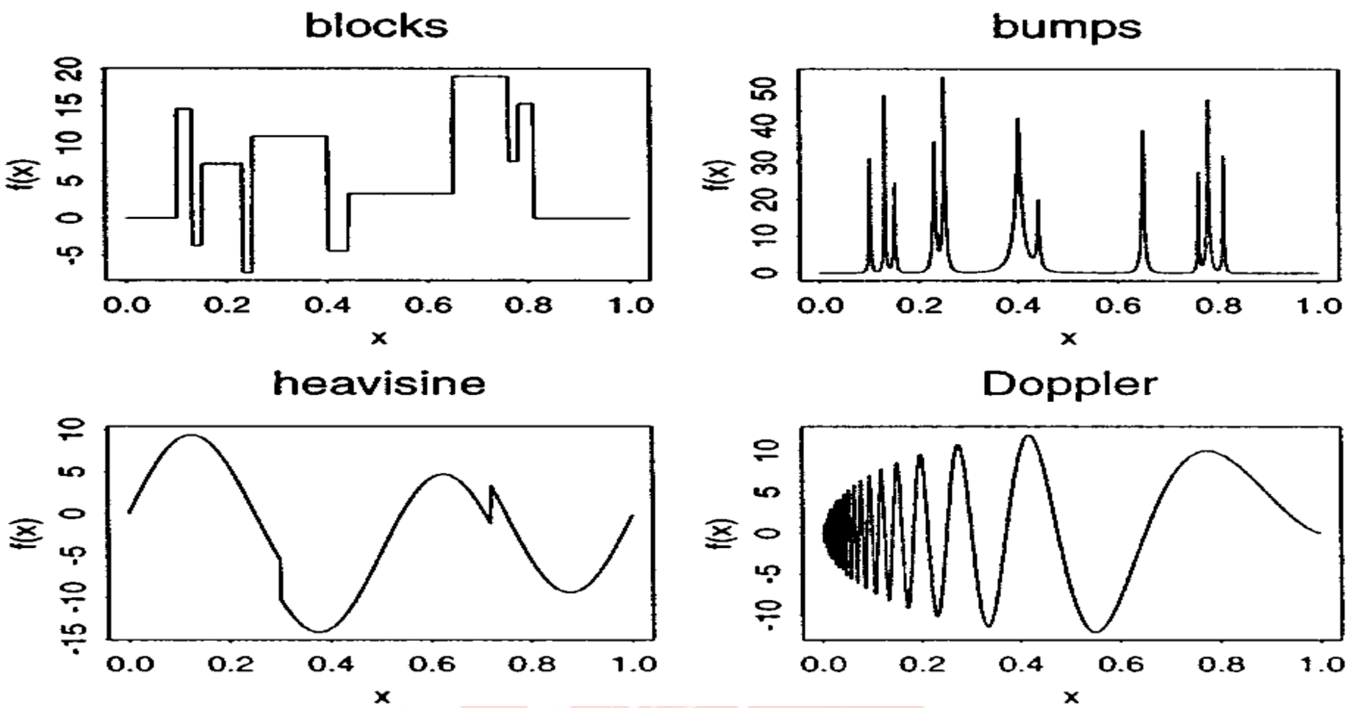

Fig 1. Four signals

Gabor (Blackman) and Sure Shrink, and data for Bayes Shrink generated from the MATLAB code. The test signals are called Bumps, Heavisine, Doppler, Blocks. For the three sample sizes, Ns = 512, Ns = 2048, and Ns = 8192, these signals were obtained from uniform samples over the interval $0 \le t < 1$.

TABLE 1: AVERAGE MSES ON DENOISING TEST SIGNALS FOR SAMPLES Ns. GAB-G IS HARD GABOR (GAUSS), SSHR IS SURESHRINK, BSHR IS BAYESSHRINK, AND GAB-B IS HARD GABOR (BLACKMAN).

SIGNAL	Ns	GAB-G	SSHR	BSHR	GAB-B
Bumps	512	0.31	0.38	0.43	0.33
	2048	0.11	0.13	0.14	0.10
	8192	0.04	0.04	0.04	0.02
Heavisine	512	0.25	0.14	0.14	0.26
	2048	0.10	0.07	0.05	0.10
	8192	0.05	0.04	0.02	0.04
Doppler	512	0.30	0.29	0.25	0.29
	2048	0.10	0.11	0.09	0.06
	8192	0.03	0.05	0.02	0.01
Blocks	512	0.87	0.49	0.57	1.13
	2048	0.57	0.25	0.25	0.58
	8192	0.30	0.11	0.10	0.28

In Table 1, the results of comparison of MSEs for the four methods are shown. Averages were taken using 100 realizations of noisy signals. These results indicates outperforms both Hard Gabor (Gauss) and Sure Shrink on two-thirds of the data, and outperforms Bayes Shrink on slightly more than half the data.

One advantage, method is extremely simple where it does not employ advanced Bayesian statistical modelling like Bayes Shrink, hence there is room for improvement.

Wave shrink and Basis pursuit of Wavelet Transform: Wave shrink and basis pursuit are two nonparametric expansion based estimators, represented by a linear combination of wavelet basis functions, namely where are the wavelet coefficients. Wave shrink is defined for orthonormal wavelets only whereas basis pursuit can also use an “over complete” basis .The goal of Wave shrink and basis pursuit is to estimate the wavelet coefficients to have a good mean squared error MSE where the expectation is taken over.

Waveshrink uses orthonormal wavelets, which has two important consequences: First, the least squares estimate is simply, where is the matrix of discretized , and denotes the transpose of; second, is an unbiased estimate of , and its covariance matrix is so that the estimated least squares coefficients are independent if the noise is Gaussian. For Gaussian noise, the shrinkage can be applied to component-wise because its components are independent.

TABLE 2: RELATIVE PREDICTIVE PERFORMANCE OF BASIS PURSUIT (c = ∞) AND ROBUST BASIS PURSUIT (c = 2:0; c = 1:345). (G: GAUSSIAN; C: CONTAMINATED; T: STUDENT)

N	C	BLOCKS			BUMPS		
		G	C	T	G	C	T
1024	∞	46	109	137	47	103	130
	2.0	77	103	114	190	220	240
	1.345	141	167	179	860	884	913
4096	∞	21	69	91	18	62	85
	2.0	33	44	49	24	35	38
	1.345	58	67	72	104	114	109
N	C	HEAVISINE			DOPPLER		
		G	C	T	G	C	T
1024	∞	17	71	91	33	85	109
	2.0	17	27	33	34	49	58
	1.345	20	26	30	47	59	67
4096	∞	7	50	68	11	55	76
	2.0	7	11	13	11	17	20
	1.345	9	11	12	15	19	22

Here, one performed a Monte Carlo experiment to evaluate the relative performance of the non robust and robust wavelet-based estimators with three noise scenarios:

- (G) standard Gaussian noise;
- (C) a mixture of 90% Gaussian (0,1) and 10% Gaussian(0,16) at random locations;
- (T) Student noise with three degrees of freedom.

The four test functions plotted in Fig. 1: blocks, bumps, heavisine and Doppler are used, by normalize them such that their "standard deviation" is equal to 7.

$$\int_0^1 \left(f(x)-\bar{f}\right)^2 dx = 49$$

Where $\bar{f} = \int_0^1 f(x)\,dx$ [14]

Choosen two sample sizes of N=1024 and N=4096, and the "s8" wavelet packet dictionary with all but four levels. The minimax smoothing parameters are 2.232 and 2.594.

For each combination of noise (G, C, T) of underlying function (*blocks, bumps, heavisine, Doppler*), of sample size (N=1024 and N=4096), and of procedure (non robust , robust), it is estimated the MSE by averaging (40)(1024)/N model errors (i.e., 40 for N = 1024 and 10 for N = 4096 to get the same number of points is generated for the two sample sizes).

Here, achieved on a particular simulation that robust basis pursuit has a good predictive performance with both Gaussian and long-tailed symmetric additive noise; in particular, it is recommended using a cut point of at least c=2 for the Huber loss function. As illustrated with two applications, robust basis pursuit has a definite advantage over both a non robust wavelet-based estimator and a median filter estimator.

III. CONCLUSION

In this paper, analyzing methods for denoising of one dimensional signals, Hard Gabor (Blackman), outperforms and Sure Shrink for two thirds of tested data, and outperforms Bayes Shrink on slightly more than half of tested data. A particular simulation that robust basis pursuit has a good predictive performance with both Gaussian and long-tailed symmetric additive noise. As illustrated with two applications, robust basis pursuit has a definite advantage over both a non robust wavelet-based estimator and a median filter estimator.

REFERENCES

[1] Signal Denoising with Interval Dependent Thresholding Using DWT and SWT, Ramesh Kumar, Prabhat Patel International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-I, Issue-6, November 2012.

[2] Noise Smoothing for Structural Vibration Test Signals Using an Improved Wavelet Thresholding Technique Ting-Hua Yi,Hong-Nan Li and Xiao-Yan Zhao.

[3] Signal Denoising Using Wavelets Rami Cohen February 2012.

[4] Signal Denoiser Using Wavelets And Block Matching Process B. Jai Shankar, K. Durai swamy Asian Journal Of Computer Science And Information Technology2: 1 (2012) 1 – 3.

[5] A New Wavelet Threshold Determination Method Considering Interscale Correlation in Signal Denoising Can He, Jianchun Xing, Juelong Li, Qiliang Yang, and Ronghao Wang,Hindawi Publishing Corporation Mathematical Problems in Engineering Article ID 280251
[6] A New Signal Denoising Method using Iterative Thresholding of the Spectral Intrinsic Decomposition Oumar Niang, Abdoulaye Thioune, Mouhamed Cheikh El Gueirea, Eric De echelle and Jacques Lemoine. IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 6, No 3, November 2012.
[7] A Wavelet Based Denoising of Speech Signal V.S.R Kumari, Dileep Kumar Devarakonda International Journal of Engineering Trends and Technology (IJETT) – Volume 5 number 2 - Nov 2013.
[8] A Signal Denoising Method For Full-Waveform Lidar Data Mohsen Azadbakht, Clive S. Fraser, Chunsun Zhang, Joseph Leach bisprs Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume II-5/W2, 2013.
[9] A comparison of denoising methods for one dimensional time series Torsten kohler, Dirk Lorenz.
[10] Denoising of Audio Data by Nonlinear Diffusion Martin Welk, Achim Bergmeister, and Joachim Weickert.
[11] Generalized methods and solvers for noise removal from piecewise constant signals. By Max A. Little And Nick S.Jones in rspa. royal society publishing April 8, 2015.
[12] On The Equivalence Of Soft Wavelet Shrinkage, Total Variation Diffusion, Total Variation Regularization, And Sides. Gabriele Steidl, Joachim Weickert, Thomas Brox, Pavel Mr Azek, And Martin Welk Siam J. Numer. Anal.2004 Society for Industrial and Applied Mathematics Vol. 42, No. 2, pp. 686–713.
[13] Denoising Gabor Transforms, James S. Walker and Ying-Jui Chen, Member, IEEE.
[14] Robust Wavelet Denoising, Sylvain Sardy, Paul Tseng, and Andrew Bruce.