



# An Iterative Time Domain Denoising Method

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# Introduction

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- ▶ The classic signal restoration problem is to determine the ideal signal  $x(n)$  from the detected signal  $y(n)$  given by the additive model

$$y(n) = p(n) * x(n) + \eta(n) \quad (1)$$

where  $p(n)$  denotes the impulse response of the data acquisition system, the asterisk (\*) represents linear convolution, and  $\eta(n)$  is a random process.

- ▶ The noise samples  $\eta(n)$  are generally assumed to be white and Gaussian distributed.
- ▶ The noise is typically assumed to be independent of  $x(n)$ .

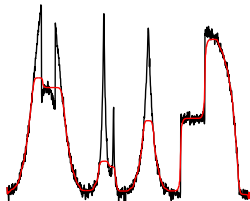
# Some Previous Methods to Remove Noise

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- ▶ averaging filters
- ▶ adaptive median filters
- ▶ Weiner filter
- ▶ Wavelet Thresholding
- ▶ Empirical Mode Decomposition Interval Thresholding (EMT-IT)

# Iterative Mean Filters

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- ▶ Black is original signal with additive noise.
- ▶ Red is the result of an iterative averaging filter, the Squeeze Box Filter (SBF)
- ▶ Pros
  - ▶ Accurate when the signal is smooth.
- ▶ Cons
  - ▶ Diminishes sharp edges, peaks, and valleys.

# SBF with Thresholding (SBFT)

- 1) Set iteration indices  $i, j = 0$  and  $y_{i,j}(n) = y(n)$ .
- 2) Set iteration limits  $\lambda_1, \lambda_2 > 0$ , thresholds  $T_{i,1}, T_{i,2} \geq 0$  for  $i = 0, 1, 2, \dots, \lambda_2$ , and convergence criteria  $\epsilon > 0$ .
- 3) Each iteration  $j$  ( $j$  starts at one) begins by determining the set of locations of local maxima (peaks) and local minima (valleys).  
The locations of these extrema are defined by the set

$$\mathcal{N}_E = \{n \mid y_{i,j-1}(n) \text{ meets condition 1 or 2} \}$$

Condition 1:  $y_{i,j-1}(n) > y_{i,j-1}(n-1)$  and  $y_{i,j-1}(n) > y_{i,j-1}(n+1)$

Condition 2:  $y_{i,j-1}(n) < y_{i,j-1}(n+l)$  and  $y_{i,j-1}(n) < y_{i,j-1}(n+1)$

- 4) Without using the local extrema values, samples within an odd length  $L$  window centered at  $y_{i,j-1}(n)$  are used to determine the local mean. These extrema may be replaced with the local mean values. That is for  $n \in \mathcal{N}_E$  the local mean is computed as:

$$\bar{y}_{i,j-1}(n) = \frac{1}{L-1} \left( \left( \sum_{l=-\lfloor \frac{L}{2} \rfloor}^{\lfloor \frac{L}{2} \rfloor} y_{i,j-1}(n+l) \right) - y_{i,j-1}(n) \right)$$

where  $\lfloor \cdot \rfloor$  is the greatest integer function.

- 5) The minimum and maximum values within the length  $L$  window centered at  $y_{i-1}(n)$  are determined

$$m = \min \left( \left\{ y_{i,j-1}(n+l) \mid l = 0, \pm 1, \pm 2, \pm \left\lfloor \frac{L}{2} \right\rfloor \right\} \right)$$

and

$$M = \max \left( \left\{ y_{i,j-1}(n+l) \mid l = 0, \pm 1, \pm 2, \pm \left\lfloor \frac{L}{2} \right\rfloor \right\} \right).$$

- 6) The outlier maybe replace according to

$$y_{i,j}(n) = \begin{cases} y_{i,j-1}(n) & \text{if } |M - m| \geq T_{i,1} \text{ or} \\ & |\bar{y}_{i,j-1}(n) - y_{i,j-1}(n)| \geq T_{i,2} \\ \bar{y}_{i,j-1}(n) & \text{otherwise.} \end{cases}$$

7a) If  $j < \lambda_1$  and convergence in the Cauchy sense is not attained, that is

$$\sum_{n=0}^{N-1} |y_{i,j-1}(n) - y_{i,j}(n)| > \epsilon, \quad (2)$$

then  $j$  is incremented by one and another iteration, starting from Step 3, is performed.

7b) If  $j = \lambda_1$  or Cauchy convergence, is attained, then when  $i < \lambda_2$ ,  $i$  is incremented by one,  $j = 0$ , and

$$y_{i,j}(n) = y_{i-1,\lambda_1}(n) * h(n)$$

where  $h(n)$  is a low pass filter. The process continues starting at Step 3.

8) The algorithm stops when  $i = \lambda_2$ . An approximation of the noise free signal is produced as

$$\hat{y}(n) = y_{\lambda_2,\lambda_1}(n).$$

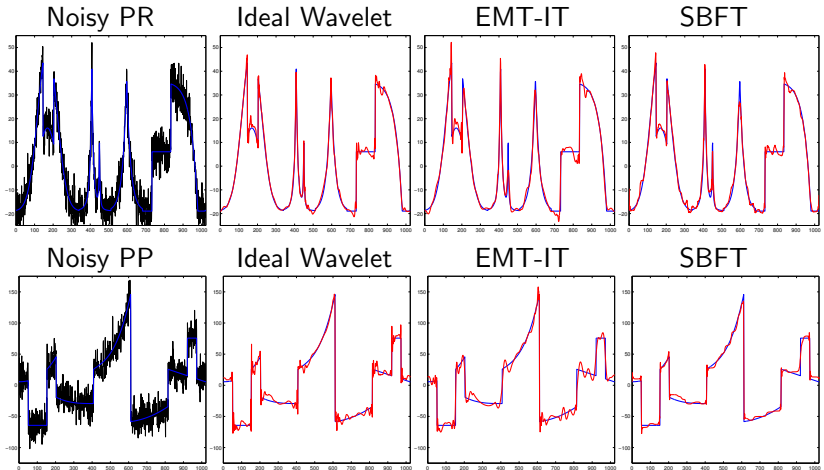
# Experiment

- ▶ Compared SBFT with
  - ▶ Ideal wavelet, wavelet denoising with hard and soft thresholding from Wavelab 850 found at <https://statweb.stanford.edu/~wavelab/>
  - ▶ EMD-IT from Y. Kopsinis and S. McLaughlin, Development of EMD-based denoising methods inspired by wavelet thresholding, *IEEE Trans. Signal Processing*, vol. 57, no. 4, pp. 18471860, April 2009.
- ▶ Wavelab 850 test signals used
  - ▶ Piece-Regular (PR) with additive Gaussian noise of  $\sigma = 5$ .
  - ▶ Piece-Polynomial (PP) with additive Gaussian noise of  $\sigma = 5$ .
  - ▶ Blocks (BL) with additive Gaussian noise of  $\sigma = 1$ .
  - ▶ Doppler (DP) with additive Gaussian noise of  $\sigma = 0.1$ .
- ▶ SBFT parameters

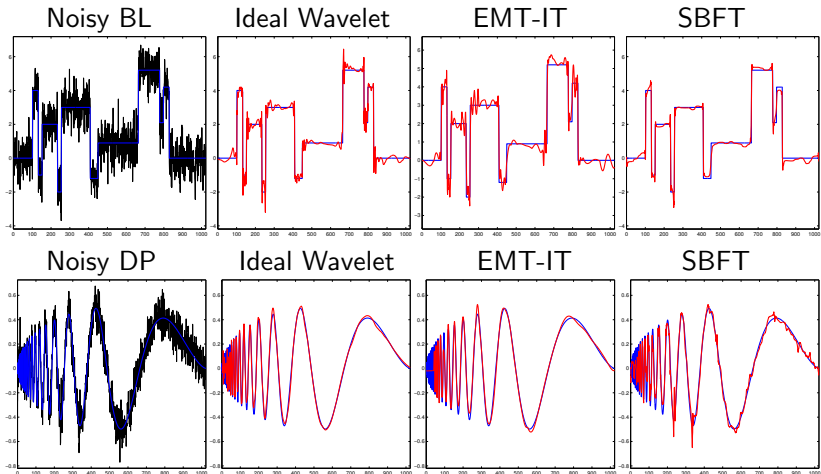
	PR	PP	BL	DP
$\lambda_1$	3	45	30	2
$T_{0,1}$	21	70	4	0.34
$T_{0,2}$	18	60	2	0.35
$T_{1,1}$	12	40	2.4	0.29
$T_{1,2}$	5	25	1.4	0.13



# Results



# Results



# Signal to Noise Ratio (SNR)

►  $\text{SNR} \{\hat{\mathbf{y}}\} = 20 \log_{10} \left( \frac{\|\mathbf{x}\|}{\|\mathbf{x} - \hat{\mathbf{y}}\|} \right)$  dB

where  $\mathbf{x}$  is the noise free signal and  $\hat{\mathbf{y}}$  is the reconstructed signal.

Method	WaveLab Signal			
	PR	PP	BL	DP
unprocessed	11.30	10.49	10.05	9.65
wavelet-ST	12.24	16.13	9.61	11.42
wavelet-HT	18.05	12.61	14.89	18.31
EMD-IT	18.26	16.24	16.48	18.51
SBFT	20.50	18.53	19.64	16.37
Ideal Wavelet	22.83	18.71	19.59	20.58

# Conclusion

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- ▶ The SBFT incorporates a thresholding operation into the iterative averaging SBF algorithm to preserve a signal's peaks and valleys, while the additive noise is being reduced.
- ▶ The results show the proposed SBFT is capable of in excess of 2 dB SNR improvement over the wavelet-ST, wavelet-HT, and EMD-IT methods on certain signals.
- ▶ In the PP restoration the SBFT nearly attained the same SNR as the ideal wavelet method.
- ▶ In the BL example the SNR of SBFT exceeds the SNR of the ideal wavelet method and provided over 3 dB improvement over the others.
- ▶ When restoring the band limited DP signal, the SBFT did not perform on par with wavelet-HT and EMD-IT where the subband decomposition may have been advantageous.
- ▶ The evidence provided shows that the SBFT may be a more robust denoising method than subband decomposition based methods with certain signals.

# Thank you!!!

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Questions?