Noise Reduction in Lidar Signals Using Interval-Thresholded Empirical Mode Decomposition

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Outline



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- Inversion
- Empirical Mode Decomposition

3 Methods

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- Test Cases

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- 6 Acknowledgments



The Problem

Lidar requires a high signal-to-noise ratio to measure scattered laser pulses against the atmospheric and electronic backgrounds.

Noise Considerations

- Inversion process causes noise to become non-linear and non-stationary
- Sources of noise are difficult to completely eliminate.

Inadequate Solutions

- Statistical methods work against lidar's strengths by degrading resolution.
- Signal processing methods of denoising attempt to rebuild the signal instead of removing noise.



HU Lidar



HU Lidar

Lidar Equation

$$P(R) = C\left[\frac{O(R)}{R^2}\right]\beta(R)\exp\left\{-2\int_0^R \alpha(r)\,dr\right\}$$

[Fernald et al., 1972]

Performance - SNR Concerns

- Decreasing power with increasing range
- Decreasing scatterer densities with increasing range

Sources of Noise

- Poisson (Counting) Errors
 - Solar Background
 - Electrical/System noise (as above)



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Inversion

Fernald Inversion (Aerosol Extinction/Backscatter) [Fernald et al., 1972; Klett, 1981; Sasano et al., 1985]

• Differential Equation solution to the lidar equation

$$\beta_{a}(R) = -\beta_{m}(R) + \frac{X(R)\exp\left\{-2\int_{R_{0}}^{R} [L_{a}(R) - L_{m}]\beta_{m}(r) dr\right\}}{\frac{X(R_{0})}{\beta_{a}(R_{0}) + \beta_{m}(R_{0})} - 2\int_{R_{0}}^{R} L_{a}(r)X(r)T(R_{0}, r)}$$

Limitations

- Requires a reference altitude of known backscatter coefficient or backscatter ratio. (1%Error → x10 [Russell et al., 1979])
- Noise becomes a non-stationary with a near-linear dependency on range. (Logarithmic R² dependency [Klett, 1981])
- Integration is more stable in the backwards direction than forward [Sasano et al., 1985]

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Inversion



Inversion



ЕВТ



EMD

EMD Sifting Process

Produce basis functions via an intuitive, direct, *a posteriori*, and adaptive technique. [Huang et al., 1998] Assumptions

- The signal has at least two extrema (Maximum + Minimum)
- The characteristic time scale is defined by the time lapse between the extrema
- If the data are devoid of extrema, containing only inflection points, differentiation will reveal extrema.

Stopping Criteria

$$\mathsf{SD} = \sum_{t=0}^{T} \left[\frac{\left| h_{1(k-1)}(t) - h_{1k}(t) \right|^2}{h_{1(k-1)}^2(t)} \right]$$

EMD

EMD Denoising

- Current application to lidar is rudimentary [Liu et al., 2008; Wu et al., 2006; Zhang et al., 2010; Zhao and Colony, 2001].
 - The first set of IMFs are discarded as completely noise.
 - Cutoff may be arbitrary or determined via power spectra.
 - Filtering (Savitzky-Golay) may be applied instead of directly discarding IMFs.
 - Direct thresholding as in wavelet has also been applied [Boudraa, 2004; Gong et al., 2011].

Limitations

- Discarding IMFs can lead to loss of structure or introduction of oscillations.
 - Reconstructing a non-periodic signal with periodic components.
- Direct thresholding on continuous IMFs introduces errors.

Methods

EMD Thresholding [Donoho and Johnstone, 1994; Kopsinis and McLaughlin, 2008]

- Each IMF is denoised using a thresholding technique.
 - Thresholding is applied based on the interval between zero crossings
- Signal is suppressed by a thresholding parameter (τ) if outside $\pm \tau$, and zeroed otherwise (Soft-T).
 - Similar to wavelet thresholding; Interval scaled accordingly.
 - Since IMFs are continuous function, any extrema outside the threshold preserves the points inside the threshold (Interval Thresholding) [Kopsinis and McLaughlin, 2008].
- Denoised signal is generated from the sum of the denoised IMFs. $(S^*(t) = \sum c_i^*(t))$

• Note: $S(t) = \sum c_i(t)$.

• Preserves major, yet highly localized, features in noise (high frequency) components.

EMD Thresholding

EMD-CIIT [Kopsinis and McLaughlin, 2009]

- EMD acts as a dyadic filter, so first IMFs contain almost all of the noise [Flandrin et al., 2004].
- Virtually resample the signal by randomly circulating the 1st noise-dominant IMF with a reconstruction from the remaining denoised IMFs. **Think Bootstrapping!**
- Perform EMD on each resample and average for a potentially better signal estimate.
 - Filter using wavelet before permutation since first IMF might contain information (thin aerosol/cloud layers).



Modeled Signal

- Generate base signal using lidar equation and normalize to maximum of 100.
- Only include molecular scattering from U. S. Standard Atmosphere 1976 [NOAA, 1976]
- 3 Gaussians added to simulate aerosol/cloud features
- Add noise with $\mu = 0, \sigma = 0.1\% \max[P(R)]$

Measured Signal

- 532 nm signal from 20 July 2011 at 13:41:42 EST
- 20 July 2011 1064 and 532 nm Aerosol Extinction Coefficients
- 19–20 April 2012 Raman Temperature Profiles
- 21 April 2012 1064 and 532 nm PBL Heights





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Retrieved Signal at 532 nm on 20 July 2011 at 13:41:42 EST



CREST

Results - Simulated Signal Tests



REST

Results - Simulated Signal Tests



CREBT

Results - Simulated Signal Tests

2-Sample Anderson-Darling p-Values: Injected Noise vs. Traditionally Removed Noise for Modeled Signal

	Technique						
	Mean2	Mean4	WV4	WV6	WV8		
PAD	0.00	0.00	0.09	0.12	0.12		

2-Sample Anderson-Darling

- Hard-Thresholded EMD-IT passes for $\tau_{mult} \in [0.5, 1.5]$
 - Some dependence on $N_{\rm sifts}$ with best results between 15–17
- Soft-Thresholded EMD-IT passes beginning at $\tau_{\rm mult} = 0.4$ to variably between 0.5–0.9.
- Hard-Thresholded EMD-CIIT passes unifromly from $au_{mult} \in [0.6, 1.5]$
- Soft-Thresholded EMD-CIIT passes from $\tau_{mult} = 0.4$ to 1.1–1.3.
 - No significant dependence on N_{sifts} . Significant gains from N_{circ} converging quickly after 80.

Results - 532 nm Signal Tests

Denoised Signal-to-Noise Ratio 110 -IT-H IT-S 105 CIIT-H CIIT-S 100 -Mean2 Mean4 95 -WV4 Å SNR 90 85 · $N_{sifts} = 25$ 80 $N_{circ} = 800$ 75 -70 0.1 0.3 0.5 0.7 0.9 1.1 1.3 1.5 τ_{mult}

REST

Results - 532 nm Signal Tests

1-Sample p-Values: Injected Noise vs. Traditionally Removed Noise for 20 July 2012 532 nm Signal

	Technique							
	Mean2	Mean4	WV4	WV6	WV8			
PAD	0	0	1.330×10^{-20}	9.412×10^{-18}	6.446×10^{-12}			
PSW	3.701×10^{-90}	5.492×10^{-90}	1.207×10^{-22}	6.350×10^{-22}	1.453×10^{-18}			

1-Sample Anderson-Darling and Shapiro-Wilk Tests

- Hard-Thresholded EMD-IT has no consistent values between tests.
- Soft-Thresholded EMD-IT passes consistently for $\tau_{\rm mult}=$ 0.4.
- Hard-Thresholded EMD-CIIT passes unifromly from $\tau_{\rm mult} \geq$ 0.7 and $\mathit{N}_{\rm sifts} \geq 15$
- Soft-Thresholded EMD-CIIT passes from $\tau_{mult} \in [0.3, 0.4]$.























Results - 20 July 2011 Aerosol Extinction



HEST

Results - 20 July 2011 Aerosol Extinction



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REST

Results - 20 July 2011 Aerosol Extinction



IEST

Results - 20 July 2011 Aerosol Extinction



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Results - 20 July 2011 Aerosol Extinction

Noise-Reduction Statistics for Denoised 1064 nm Range-Corrected Signal and Aerosol Extinction Coefficients on 20 July 2011 13:41:42

Method	σ_X	% _{Err,X}	σ_{lpha}	$%_{Err,\alpha}$	r _{full,X}	$r_{full,\alpha}$	r _{strat,X}	$r_{strat, \alpha}$
Base	1.71e+06	32.36%	5.67e-07	46.27%	1.0000	1.0000	1.0000	1.0000
Avg15				—	0.9883	0.9838	0.8594	0.8528
Avg30				_	0.9764	0.9688	0.8355	0.8277
Avg60		_		_	0.9703	0.9641	0.8138	0.8043
DB4	3.52e+05	5.87%	1.08e-07	7.86%	0.9969	0.9950	0.7896	0.7730
DB6	3.72e+05	8.80%	1.60e-07	15.98%	0.9968	0.9946	0.7691	0.7587
DB8	2.11e+05	4.39%	1.27e-07	10.14%	0.9967	0.9946	0.7590	0.7444
IT	3.65e+05	7.04%	1.20e-07	9.85%	0.9972	0.9955	0.8100	0.8009
CIIT	2.73e+05	5.19%	9.21e-08	7.53%	0.9972	0.9955	0.8128	0.8038

EMD performs at least as well as Wavelet noise reduction for overall signal

2 EMD outperforms wavelet and is comparable to long temporal averages for the stratospheric layer.



Results - 20 July 2011 Aerosol Extinction

Noise-Reduction Statistics for Denoised 532 nm Range-Corrected Signal and Aerosol Extinction Coefficients on 20 July 2011 13:41:42

Method	σ_X	% _{Err,X}	σ_{lpha}	$\mathcal{W}_{Err,\alpha}$	r _{full} ,x	$r_{full,\alpha}$	r _{strat} ,x	$r_{strat, \alpha}$
Base	1.51e+06	21.60%	4.48e-07	29.10%	1.0000	1.0000	1.0000	1.0000
Avg15	—	—			0.9906	0.9879	0.7971	0.7934
Avg30	—	_	—	_	0.9375	0.9299	0.7075	0.7018
Avg60	—	_	—	_	0.9777	0.9722	0.7733	0.7691
DB4	2.59e+05	3.51%	5.70e-08	3.68%	0.9976	0.9963	0.6737	0.6671
DB6	1.96e+05	3.10%	5.37e-08	3.90%	0.9975	0.9962	0.6571	0.6539
DB8	2.60e+05	3.99%	6.62e-08	4.28%	0.9974	0.9959	0.6447	0.6383
IT	3.67e+05	5.27%	1.17e-07	7.66%	0.9978	0.9968	0.7462	0.7414
CIIT	2.95e+05	4.24%	7.75e-08	5.03%	0.9979	0.9968	0.7422	0.7369

 \blacksquare EMD (esp. CIIT) performs comparably to wavelet in reducing signal σ

- EMD outperforms wavelet and is comparable to long temporal averages for the stratospheric layer.
 - Particularly true for stratospheric layer.



Conclusion I

- Appropriate values for EMD-based denoising have been determined
 - $\tau_{\text{mult}} \in [0.3, 0.5]$ for Soft Thresholding
 - $\tau_{mult} \in [0.7, 1.1]$ for Hard Thresholding
 - $N_{\rm sifts}$ only significant for IT, \approx 16 ideal.
 - Small N_{circ} for CIIT shows significant benefits (< 100). More siftings provides smoother signal.
- EMD-based denoising performs at least as well as traditional techniques
 - Higher SNR
 - Lower errors
 - Higher resolution than averaging and wavelet.
- EMD-based denoising introduces fewer artifacts into the resulting signal



Conclusion II

- Offers potentially large benefits to incredibly low SNR signals when combined with averaging techniques
 - Reduces the number of averaging bins required.
- Offers the least error in removing significant physical signal components.
- Still significant work for optimizing the technique to varying levels of signal SNR.
 - e.g. Raman Temperature vs. 532 nm Extinction vs. 1064 nm Extinction
 - Applications to other atmospheric measurements worth exploring.



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BACKUP SLIDES



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EMD

Empirical Mode Decomposition [Huang et al., 1998]

- Decompose signal into Intrinsic Mode Functions (IMFs)
 - Functions whose local extrema differ from the total number of zero crossings by at most 1, and the mean value of an envelope enclosing those maxima and minima is 0.
- Sifting Process
 - Cubic spline interpolate through maxima and minima to create two envelopes.
 - Subtract mean of the envelopes from the signal and test result for IMF criteria. $(h_{1,1} = S(t) m_{1,1})$
 - 3 Algorithm continues until result is an IMF. $(c_1 = h_{1,n})$
 - c_1 is subtracted from S(t) and the process continues on the remainder r_1 .
 - Process stops when r_n is an IMF or cannot be sifted into an IMF.
- IMFs represent (instantaneous) frequency components of the signal.







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Noise-Reduction Statistics for Denoised Temperature Profiles									
Measured 19–20 April 2012									
Method	20 Ap	ril 2012, (00:00	20 April 2012, 21:00					
Methou	σ_T	RMSE	r _T	σ_T	RMSE	r _T			
Base	10.763	0.226	0.774	11.992	0.245	0.793			
Avg15	10.062	0.117	0.951	9.839	0.103	0.965			
Avg30	10.180	0.100	0.968	9.942	0.092	0.976			
Avg60	10.117	0.085	0.978	9.773	0.071	0.985			
DB4	10.026	0.101	0.959	10.064	0.104	0.967			
DB6	9.936	0.104	0.959	9.979	0.098	0.968			
DB8	10.130	0.104	0.962	9.882	0.104	0.960			
IT	10.280	0.143	0.934	10.167	0.137	0.925			
CIIT	10.242	0.114	0.958	10.107	0.111	0.962			

Noise Deduction Statistics for Densignal Temperature Drafiles









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