WAVELET SIGNAL DENOISING APPLIED TO MULTIWAVELENGTH-DEPOLARIZATION WHITE LIGHT LIDAR MEASUREMENT

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ABSTRACT

Wavelet denoising was applied to white light lidar signals using several wavelet functions. For the strong 550 nm and 700 nm backscattered signals, all the wavelets applied for denoising gave the same high correlation, γ, with the 800 nm signal. However, for the weaker 350 nm and the 450 nm backscattered signals, Daubechies 5 gave a high %increase in γ. Cloud signals that were buried in noise in the weaker channels became noticeable after the denoising procedure. The result of the study showed that wavelet signal denoising could improve the detectable range of the white light lidar system presented in this study. Daubechies 5 wavelet function was found to be the most suitable for denoising the backscattered white light lidar signals.

1. INTRODUCTION

Supercontinuum generation on air and other gas media using high peak power femtosecond lasers opened the way for multispectral atmospheric remote sensing using a white light lidar. Because of its broad spectrum ranging from UV to IR, the technique offers several applications [1,2]. Just recently we demonstrated that the coherent white light continuum can be used for depolarization measurement in the same way as the conventional lidar [3]. The white light continuum was generated in a 9-m long Kr gas cell before transmitting to the atmosphere. The receiving system detects lidar signal at 5 wavelengths (350, 450, 550, 700, and 800 nm) with depolarization measurement at 450 nm. The complete description of the system can be found in [3]. In the present system, the detected signals at 350 nm and 450 nm are sometimes very weak. Cloud signals that are noticeable in 550, 700 and 800 nm lidar signals are sometimes hardly noticeable in the 350 and 450 nm lidar signals because they are buried in noise. The transmitted intensity of the white light was very weak for shorter wavelengths [2,3]. The Lidar system itself produced random noise and interference which are usually smoothen by means of the moving average method over the distance but it does not remove the noise. High currents that are switched in the laser circuits during the pulse produced a time-dependent background noise which are usually difficult to eliminate by simple shielding [4]. Other sources of noise in lidar signals are background noises from Sun and Moon. Recently, the wavelet transform has become an efficient data analysis tool in many fields such as estimation, classification, and compression, etc [4]. It has become a powerful tool for detecting signals buried in noise and interferences. Wavelet denoising is a noise reduction method by transforming noisy data into the wavelet domain, applying thresholding in the wavelet domain, and inverse transforming the denoised wavelet coefficients [5]. Fang and Huang made a study on noise reduction in lidar signals using discrete wavelet transform [4] and wavelet neural network [6]. Wavelet analysis on cloud radar and lidar data was used to locate and size characteristic clouds elements [7]. In this paper, wavelet signal denoising applied to white light lidar signal is presented. Several wavelets were used in this study to find the most suitable wavelet for the present white light lidar system. These wavelets were Haar, Daubechies 2 (db2), 5 (db5), and 8 (db8), Symlets 2 (sym2), 5 (sym5), and 8 (sym8), and Coiflets 2 (coif2) and 5 (coif5). A six level decomposition was done on all the wavelets except for Haar in which an eight level decomposition was used. The denoising was done using one dimensional discrete wavelet analysis.

2. WAVELET TRANSFORM AND DENOISING

2.1 Brief Introduction To Wavelet Transform

In this paper, only some key equations and concepts of wavelet transform will be presented. A more detailed discussion on this topic can be found in [4-9]. A wavelet is a small wave, which has its energy concentrated in time, and a tool meant for analysis of transients and non-stationary or time varying signals. A continuous-time wavelet transform (CWT) of a signal x(t) is defined as [9]

$$CWT_x^{\psi}(\tau,s)=\frac{1}{\sqrt{|s|}}\int x(t)\psi^*\frac{(t-\tau)}{s}dt\,. \tag{1}$$

The analysis function $\psi(t)$, the so-called mother wavelet, is scaled by the scaling function, s, so a wavelet analysis is often called a time-scale analysis rather than a time-frequency analysis. The asterisk denotes a complex conjugate and this multiplication of $1/\sqrt{|s|}$ is for energy normalization purposes so that the transformed signal will have the same energy at every scale. CWT is often redundant and computationally expensive. The discrete wavelet transform (DWT), on the other hand, provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time. In DWT, a signal is essentially the decomposition of the signal into a number of levels. A signal of length 2^N can be decomposed into N+1 levels. The next step after the decomposition is to reconstruct the signal by adding all the levels. For further details, please refer to [8,9,10].

The differences between different mother wavelet functions (e.g. Haar, Daubechies, Coiflets, Symlets, and etc.) consist in how these scaling signals and the wavelets are defined. The different wavelet functions used in this study are shown in Fig.1. Haar wavelet is discontinuous, and resembles a step function. Daubechies are called compactly supported orthonormal wavelets making discrete wavelet analysis practicable The names of

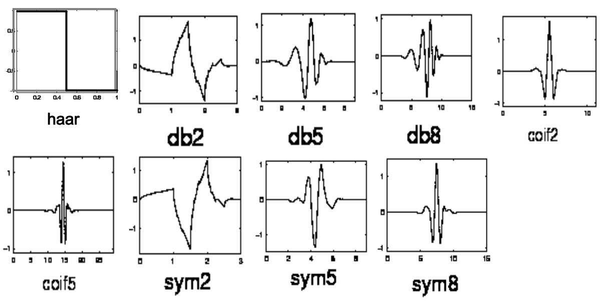

Fig. 1. The different wavelet functions used in this study.

the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet is the same as Haar wavelet. Coiflet is the wavelet function that has 2N moments equal to 0 and the scaling function has 2N-1 moments equal to 0. The two functions have a support of length 6N-1. The Symlets are nearly symmetrical wavelets proposed by Daubechies [11] as modifications to the db family. The properties of the two wavelet families are similar.

2.2 Wavelet-based Denoising Procedure

The general wavelet denosing procedure is as follows:

• Apply wavelet transform to the noisy signal to produce the noisy wavelet coefficients to the level which we can properly distinguish cloud signals that are present in the strongest lidar signal (in this case, the 800 nm channel) from the weaker lidar signals (350 and the 450 nm channels). In this work different levels were tried and a six decomposition-reconstruction level was found to be sufficient in all lidar signals.

• Select appropriate threshold limit at each level and threshold method (hard or soft thresholding) to best remove the noises. Since the lidar signal tends to dominate low-frequecy components, soft thresholding was selected as suggested in [4].

• Inverse wavelet transform of the thresholded wavelet coefficients to obtain a denoised signal.

2.3 Wavelet Selection

To best distinguish the cloud signals in a noisy lidar signal, the “mother wavelet” should be selected carefully to better approximate and capture the cloud signals. The choice of mother wavelet was based on visual inspection of the lidar signals and based on correlation γ between the denoised lidar signal at 800 nm and the wavelet-denoised signal of the other 4 wavelengths. The correlation coefficient is given by

$$\gamma_{X,Y} = \frac{\frac{1}{n}\sum_{j=1}^{n}\left(X_j - \overline{X}\right)\left(Y_j - \overline{Y}\right)}{\sigma_X \sigma_Y} \quad (2)$$

Where X and Y are the data being compared, $\overline{X}$ and $\overline{Y}$ are the mean values, and σ is the standard deviation.

3. THE WHITE LIGHT LIDAR SYSTEM

The setup of the white light lidar sytem is shown in Fig. 2. The lidar system is in biaxial configuration. The laser transmitter consists of a tabletop terawatt Ti:Sapphire laser sytem which operates at 800 nm. It has a frontend, which is a combination of a Ti:Sapphire oscillator pumped by a laser diode (LD) pumped green Nd:YVO4 CW-laser and a regenerative amplifier pumped by a LD-pumped green Nd:YLF laser operated at 1 kHz. The output of the frontend is a 100 fs pulse with an energy

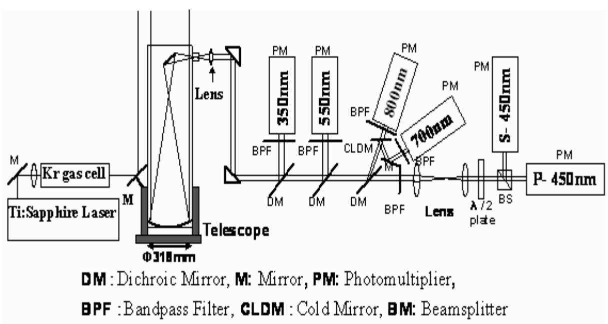

Fig. 2. Experimental setup of the white light lidar system.

of 0.8 mJ. The uncompressed frontend pulse is introduced to a multipass Ti:Sapphire amplifier which is pumped by two frequency doubled Nd:YAG lasers. The final output energy is 100 mJ with a pulsewidth of 100 fs at a repetition rate of 10 Hz. To generate the white light, output from the Ti:Sapphire laser system is focused by a lens with a focal length of 5 m into a 9 m long traveling tube filled with Krypton gas at a pressure of 1 atm. The generated white light which has a broad spectrum from 300 nm to more than 950 nm and a linear polarization similar to the original 800 nm pulse [3] is collimated by a 10-m radius spherical mirror and transmitted vertically to the atmosphere. The backscattered light is collected by a 30-cm diameter Newtonian telescope. The output light passes along a light guide consisting of a pair of stardiagonal prisms and is then directed to a 6-channel simultaneous measurement system. This configuration preserves the polarization of the backscattered light. A more detailed description of the experiment can be found in [3].

4. RESULTS AND DISCUSSION

The measurement was carried out on March 23, 2005 at Suita, Osaka, Japan. Shown in Fig. 3 is an example of the backscattered signals from the 6-channels. A 500 shots averaging was used in each channel. It can be seen that lidar signals from 350, 450s, and 450p channels were very noisy. Using the one dimensional discrete wavelet analysis graphical interface in Matlab, each channel was denoised using Haar, Daubechies 2 (db2), 5 (db5), and 8 (db8), Symlets 2 (sym2), 5 (sym5), and 8 (sym8), and Coiflets 2 (coif2) and 5 (coif5). A six level decomposition was used except for Haar where an 8 level decomposition was applied. Automatic soft thresholding was applied in all lidar signals as suggested in [4]. Cloud peaks can be seen at 0.6 km and at 1 km. Fig. 4 shows the original lidar signals and the denoised lidar signals from 450-p, 450-s, and 350 nm channels. It can be seen from the Fig. 4 that the denoised lidar signals showed the cloud peaks especially for the 450-s channel. Both the 550 and the 700 nm channel already have a high γ with the 800 nm channel even before wavelet denoising was applied.

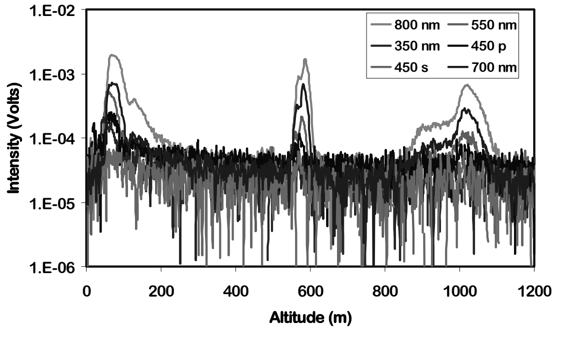

Fig. 3. An example of lidar return signal for the 5 wavelengths obtained on March 3/23/2005 at 2:11:17AM JST.

For the other three weaker channels, 350, 450s, and 450p, an increase in γ was obtained after wavelet de-

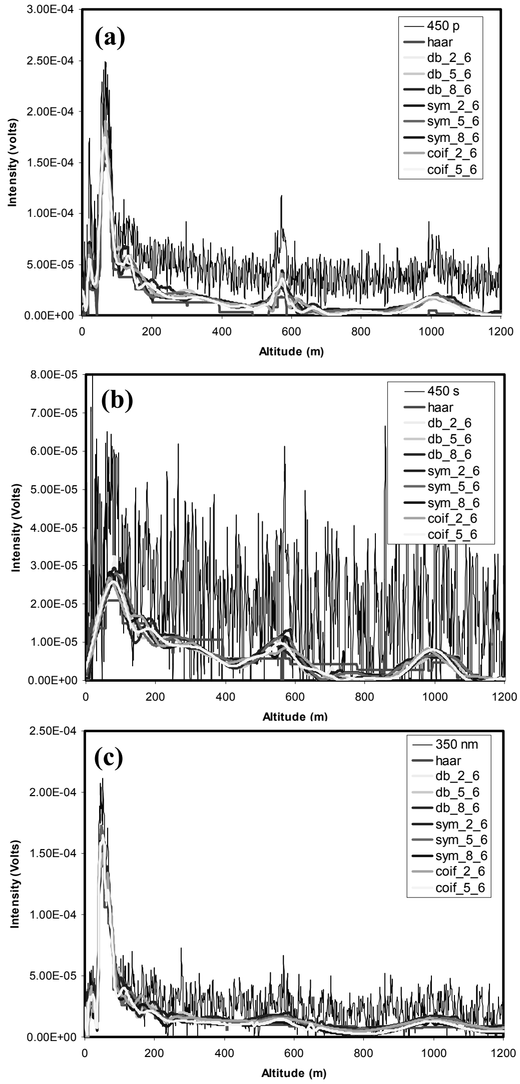

Fig. 4. The original lidar signal from the (a) 450 nm p-polarization channel; (b) 450 nm s-polarization channel; (c) 350 nm channel and the corresponding denoised lidar signals using different wavelets.

noising was applied. The correlation coefficient increase from 0.25 to 0.7, 0.6 to 0.8, and 0.43 to 0.6 for the 450s, 450p, and 350 nm channel, respectively. The 350-nm channel showed the lowest γ even after denoising as evident in Fig. 4(c). Ten other set of lidar signals, where each set contains 6 lidar signals, were denoised and their correlation with the 800 nm channel was calculated. Table 1, gives the average of the %increase in γ for each wavelength using different wavelets. The 450s lidar signal after denoising obtained the highest %increase in γ of 156%. From Table 1, db5 is consistently among the top 3 wavelets that give high γ for each channel. Visual inspection of each denoised lidar signals also indicates that db5 consistenly gives the same cloud peaks and shape found in the 800 nm lidar signal.

Table 1. The average of the %increase in γ for each wavelength using different wavelets.

Wavelet	% increase in correlation				
	450s	450p	350	550	700
Haar	81.2	20.0	21.7	4.3	0.6
Daube-chies 2	**152.0**	**27.2**	29.1	**6.7**	0.9
Daube-chies 5	**156.4**	**27.5**	**35.5**	**6.4**	**0.9**
Daube-chies 8	146.2	26.4	35.0	6.2	0.7
Symlets 2	152.8	27.0	29.4	**6.7**	0.9
Symlets 5	**154.4**	26.5	34.0	6.0	0.9
Symlets 8	141.3	**28.4**	**35.8**	6.1	0.6
Coiflets 2	134.8	26.8	**36.0**	5.8	0.6
Coiflets 5	141.4	25.2	31.0	5.9	0.9

5. SUMMARY AND CONCLUSION

Wavelet denoising was applied to white light lidar signals using several wavelets. For strong backscattered signals such as the 550 nm, 700 nm, and 800 nm, almost all the wavelets applied for denoising gived the same γ. However, for weaker 350 nm and the 450 nm backscattered signals, db5 gives high %increase in γ. Although at 350 nm, γ does not exceed 0.6. Cloud signals that were buried in noise in the weaker channels became noticeable after the denoising procedure. The result of the study showed that wavelet signal denoising can improve the detectable range of the white light lidar system presented in this study. Daubechies 5 (db5) wavelet function will be used for the denoising procedure before extracting relevant information on the backscattered signals of the current white light lidar system.

6. REFERENCES

1. Galvez, M.C.D., et al. Three-Wavelength Backscatter Measurement of Clouds and Aerosols Using a White Light Lidar System, *Jpn. J. Appl. Phys.,* Vol.41, No.3, L284-L286, 2002.

2. Rairoux, P., et al. *Appl. Phys.* B., Vol. 71, 573-580, 2000.

3. Somekawa T., et. al., Depolarization Light Detection and Ranging Using a White Light LIDAR System, *Jpn. J. Appl. Phys.,* Vol 45, No.6, pp. L165-L168, 2006.

4. Fang, H.T. and Huang, D.S, Noise Reduction in Lidar Signal Based on Discrete Wavelet Transform, *Optics Communications,* Vol. 233, pp. 67-76, 2004.

5. Ercelebi, E., Electrocardiogram signals de-noising using lifting-based discrete wavelet transform, *Computers in Biology and Medicine,*Vol. 34, 479-493, 2004

6. Fang, H.T, et al., Antinoise Approximation of the Lidar Signal with Wavelet Neural Networks, *Appl. Optics,* Vol. 44, No. 6, pp. 1077-1083.

7. Quante, M., et al, Extraction and analysis of structural features in cloud radar and lidar data using wavelet based methods, *Proceedings of ERAD*, pp. 95-103, 2002.

8. Satish, L. and Nazneen, B., Wavelet-based Denoising of Partial Discharge Signals Buried in Excessive Noise and Interference, *IEEE Transactions on Dielectrics and Electrical Insulation,* Vol. 10, No. 2, pp. 354-367, 2003.

9. Young, R.K., Wavelet Theory and Its Applications, Pennsylvania State University, Kluwer Academic Publishers, 1993.

10. R. Polikar, The wavelet tutorial,*http ://engineering. rowan.edu/~polikar/Wavelets,* 1996.

11. Daubechies, I., Ten lectures on wavelets. Philadelphia, Pa.: Society for Industrial and Applied Mathematics, 1992.