Geoinformation for European-wide Integration, Benes (ed.)
© 2003 Millpress, Rotterdam, ISBN 90-77017-71-2

Wavelet-based de-noising for derivative spectra analysis

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Keywords: hyperspectral, derivative, de-noising, wavelets

ABSTRACT: Derivative analysis is one of the techniques that is suitable for the analysis of high spectral resolution data such as that derived from airborne hyperspectral sensors and field spectrometers. The use of derivative analysis provides several advantages that facilitate the extraction of information from the data. However, the derivatives of a reflectance spectrum are significantly noisier than the original spectral reflectance curve. The advantages of derivatives are therefore offset by the introduction of such noise. A number of methods for de-noising signals have been used in the past. Our method is based on the use of wavelets. In this paper, a technique of de-noising spectra using the discrete wavelet transform is described. The de-noised derivative spectra are then used in a template-matching scheme, with image endmembers providing the templates. The result is an initial 'hard' classification of part of the study area in Central Spain using DAIS 7915 airborne hyperspectral data.

1 INTRODUCTION

Before the emergence of hyperspectral technology, remote sensing imaging systems were limited to multispectral devices, collecting data in only a few wavebands. The spectral and spatial analysis methods developed for this kind of data were based on multivariate statistics. With the availability of hyperspectral data, methods used to analyse multispectral data have been applied to hyperspectral data. However, this approach is generally considered to be inappropriate, as the multispectral analysis methods generally consider the individual spectral bands to be independent variables. This is not a suitable approach to the analysis of spectrally continuous hyperspectral data (Tsai and Philpot 1998). The traditional multispectral data analysis techniques cannot simply be extended to the hyperspectral case; more complex and specialised techniques are required.

Derivative analysis is a technique used in analytical chemistry that can reduce the effects of unwanted background interference (Fell and Smith 1982). It is also useful in extracting subtle information that might be obscured in the original data (Tsai and Philpot 2002), such as reducing the effects of differing illumination conditions (Gong *et al*. 1997). Hyperspectral remote sensing data analysis can benefit from the use of derivative analysis. However, this technique is characterised by its high sensitivity to noise in the original spectra (Galvão *et al*. 2001). Thus, smoothing or de-noising the raw spectra is often a necessary step before applying any derivative operation (Bruce and Li 2001). Several methods have been applied in smoothing noisy signals, including the Fourier transform, Savitzky-Golay, Kawata-Minami, mean filter, Gaussian function, and so on. However, these methods have several drawbacks that could reduce the effectiveness in dealing with noisy signals. Recently, a new method known as the wavelet transform has been introduced to the scientific community. It offers a much more efficient approach to signal processing. Among the major advantages of the wavelet-based de-noising method is that it can be used to reduce the level of noise while preserving the significant features of the original data (Depczynski *et al*. 1999). Barclay *et al*. (1997) compared the performance of discrete wavelet transform smoothing and de-noising methods with Savitzky-Golay smoothing and Fourier transform filtering methods and concluded that the wavelet-based methods are superior to the other methods.

In this paper, the use of wavelet-based de-noising technique is explored and applied to derivative template matching of airborne hyperspectral remote sensing data. We present the preliminary results of our research on the development of a methodology for mapping land cover based on local high spatial and spectral resolution data and the evaluation of the combination of wavelet-based de-noising and derivative analysis techniques in hyperspectral data analysis.

2 STUDY AREA AND DATA

2.1 *Study area*

The study area for this research is located within the area of 'La Mancha Alta' in central Spain. The wetland area of La Mancha Alta is regarded as one of the most important areas for migrating and wintering waterfowl in Spain (Oliver and Florín 1995). The semi-arid environment of La Mancha makes it susceptible to land degradation processes. The region, which was once famous for various types of wetlands, is now left with many destroyed wetlands due to drainage, over-pumping, and water-table decline (Grove and Rackham 2001). The exploitation of water resources has contributed to losses of wetland. Oliver and Florín (1995) report that 62.5% of La Mancha wetland areas are in the process of disappearing or have already disappeared, with only 2.8% of the wetland areas in a well-preserved state.

2.2 *DAIS 7915 airborne hyperspectral data*

The hyperspectral data used in this study was collected by the Digital Airborne Imaging Spectrometer (DAIS) 7915 airborne hyperspectral sensor. This instrument uses four spectrometers to measure radiant and emitted energy in 79 wavebands in the range 0.4 – 12.6 µm. The German Aerospace Centre (DLR) carried out the data acquisition plus radiometric, atmospheric, and geometric correction. The spatial resolution of the geometrically corrected image is 5 m. A DAIS overflight of the study area was conducted in June 2000, at the behest of the Autonomous University of Madrid.

3 METHODOLOGY

3.1 *Derivative analysis*

Derivative analysis has been applied to hyperspectral data analysis, and has been shown to yield promising results (Tsai and Philpot 1998). Derivative analysis is able to deal with the problems of quantitative remote sensing analysis in an efficient and elegant way (Demetriades-Shah *et al*. 1990). However, remote sensing data (particularly aircraft data) are acquired under uncontrolled conditions, such as changing viewing and illumination geometry, atmospheric effects, and spatial resolution factors that will result in degradation of the data due to addition of high frequency noise (Bruce and Li 2001). This situation complicates the use of derivative, as the technique is highly sensitive to noise in the data.

The first derivative measures the slope of the spectral reflectance curve at a given point. If the wavelength is denoted by x and the magnitude of spectral reflectance by y, then the derivative at any point on the curve between x_{min} and x_{max} is written as dy/dx. The simplest way to calculate the derivative for discrete (digital) data is to use the method of differences:

$$\frac{dy}{dx} = \frac{y_{j+1} - y_j}{x_{j+1} - x_j} \tag{1}$$

Higher-order derivatives are obtained by repeating the process on the derivative of the immediately lower order. However, due to the increasing sensitivity of derivatives to noise and other small random variations in the data as the derivative order increases, it is generally accepted that lower order derivatives are more suitable for operational remote sensing applications (Cloutis 1996). As the advantages of the use of derivatives are offset by the introduction of significant noise in the derivative spectrum, it is necessary to reduce the noise in the original signal before the derivative is calculated.

3.2 *Wavelet-based de-noising*

Electronic signals are affected by noise of some form, thus, before any useful analysis can be performed, it is preferred that the noise is suppressed in order not to interfere with the information content. Noise can originate from various sources such as instrumental instability, data acquisition processes, interfering natural phenomena, and so on. Thus, smoothing or de-noising is normally a necessary preprocessing step before any subsequent analysis utilising the signals is performed. This process can greatly help direct human interpretation and enhance subsequent computer-based analysis.

Various methods of signal de-noising have been used prior to derivative calculation. One of the most popular methods is the Savitzky-Golay procedure, which is used by Demetriades-Shah *et al.* (1990). The significant advantage of wavelet-based de-noising compared to other smoothing (low pass filter) methods such as Savitzky-Golay, for instance, is that wavelet-based de-noising explicitly estimates the noise variance, and differentiates between noise and signal effectively. The signal observed by the DAIS sensor could be regarded as the convolution of true signal, instrumental, electronic, and other sources of noise as well as the noise resulted from the spacing of data points, as shown in equation 2. Since the use of wavelets permits the estimation of the noise resulting from these sources, noise reduction using wavelets should be effective.

$$Signal_{Obs} = Signal_{True} + Noise_{Inst.} + Noise_{Spacing} \tag{2}$$

Another major difference between smoothing and de-noising is that smoothing methods remove only the high frequencies, whereas de-noising removes noise regardless of the frequency (Taswell 2000). This property allows wavelet-based de-noising to retain the significant information in the original signal while removing the noise.

Noise reduction is one of the many applications of wavelet analysis. Wavelet analysis is also a popular tool in performing data compression and fast computation (Bruce *et al*. 1996). Wavelet analysis can provide new information and faster performance in many scientific fields that traditionally rely on Fourier techniques. For more complicated signals of the non-stationary type, the use of Fourier transform is not applicable. The wavelet transform is suitable due to the fact that it is well adapted to non-stationary signals, such as those generally encountered in remote sensing (Ranchin and Wald 1993).

We are particularly interested in the application of wavelet-based de-noising method. Our de-noising method is based on the use of the discrete wavelet transform (DWT). DWT de-noising consists of three major steps: transformation of the noisy signal to the wavelet domain, thresholding the wavelet coefficients, and the inverse transform of the de-noised wavelet coefficients back to the original signal domain. The second step is highly critical and involves several tasks, such as the selection of the wavelet type, threshold definition, and the application of the suitable thresholding methods. Thresholding, which is an integral part in the second step, is a way of suppressing those wavelet coefficients that are below a particular threshold value. Noise is associated with these small coefficients, and thus no important information is lost. The de-noised signal is constructed from the remaining wavelet coefficients.

However, care should always be taken not to over-smooth the data as this can result in the alteration of the original and important spectral features in the data. Thus, it is always important to maintain a balance between de-noising and the preservation of the integrity of the information content of the signal.

3.3 *Template matching*

Template matching is a method of pattern recognition (Jain *et al*. 2000). Pattern recognition aims at performing supervised or unsupervised classification, which is an important issue in remote sensing. Template matching involves the determination of the resemblance of two types of entities, which can be represented in terms of points, curves or shapes. Template matching, which is conceptually and operationally simpler than the technique of linear spectral unmixing, can also be used to estimate endmember proportions. It is essentially the same as ‘cosine theta analysis’. The cosine theta measure of resemblance expresses the similarity between a reference spectrum and a target spectrum by calculating the angle between vectors representing the two spectra (Kruse *et al*. 1993). The availability of high spectral detail offered by hyperspectral data permits the use of spectral matching techniques for information extraction and classification (Schwarz and Staenz 2001).

The methodology for the wavelet-based de-noised derivative template matching of hyperspectral image data is as in figure 1.

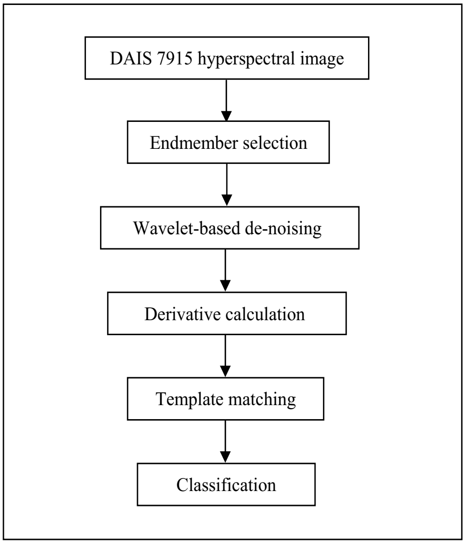

Figure 1. Processing flow of the methodology.

The first step in the methodology is to select a suitable set of bands that are continuous but which exclude the high noisy bands. DAIS reflectance data shows slight to severe striping effects from bands 41 to 47 and also from bands 57 to 72. The prominent effects of periodic noise in the longer wavelength bands of the image could also be due to the instrument’s scanning mechanism that is highly susceptible to striping (Müller *et al*. 1998). An investigation of the derivative images shows even more serious effects of periodic noise in bands 32 onwards. Furthermore, there is a considerable wavelength gap between bands 32 and 33, which renders it unsuitable for wavelet de-noising operations. Consequently, only bands 1 (0.49 μm) to 32 (1.038 μm) are considered in subsequent analysis.

The selection and identification of the image endmembers is based on the Pixel Purity Index algorithm and associated tools available in the ENVI 3.4 software package (Research Systems Inc. 2001). The wavelet-based de-noising and derivative calculation is performed using in-house MIPS image processing software. Our algorithm does not simultaneously perform smoothing and differentiation as the Savitzky-Golay polynomial curve-fitting procedure does, as this procedure might change the original curve pattern instead of removing the random noise in the signal. Consequently, artefacts could be introduced (Tsai and Philpot 1998). We calculate the de-noised signal first, then the derivative of the de-noised signal.

Since we are using a one-dimensional wavelet transform, the de-noising procedure operates in the spectral domain of the hyperspectral cube. Each pixel in the image is de-noised, and its derivative calculated. The result is a set of derivative images. Investigation of the suitability of second or higher-order derivatives indicates that second and higher-order derivatives are badly affected by high frequency noise in the data, as derivative calculation further amplifies any noise in the original signal. Thus, only the first order derivative is considered further.

The template matching algorithm calculates the degree of resemblance match between the de-noised endmember derivative spectra and all the image pixels. The template matching procedure provides a good first-cut on the spatial distribution of the major land cover types in the area, using a 'hard' classification approach.

4 RESULTS AND DISCUSSION

The methodology described above was applied to a subimage of 512 x 512 pixels taken from the DAIS hyperspectral image of the La Mancha study area. Five template spectra were used, and the output was five greyscale images showing the similarity of each hyperspectral image pixel to each of the templates. A comparison of first derivative image template matching result before and after wavelet-based de-noising was carried out to evaluate the effectiveness of the methodology. The result of template matching for the endmember 'water' is shown in figure 2. The de-noised similarity image of the water endmember is shown in figure 3. In the de-noising procedure, the mother wavelet used was the Daubechies-4 with soft thresholding using the universal threshold value. The best match of the pixel in the image to the reference template is indicated by the brightest tone.

We can see that, in the hard classification image before de-noising, the effect of striping in the data is being amplified and can be seen clearly in the greyscale image (figure 2). The effect of striping has been significantly reduced in the de-noised image with no significant degradation of the original information (figure 3). Thus, de-noising is accomplished while preserving the integrity of information in the data.

Figure 2. The greyscale image of the water endmember first derivative template matching classification before de-noising.

Figure 3. The greyscale image of the water endmember first derivative template matching classification after de-noising.

In ideal circumstances, the data series to be processed by the classical first generation wavelet transformation that we adopt in this work should be sampled at regular intervals over the spectrum (Jansen 2001). In our case, the sampling interval (distance in micrometres between band centres) varies from 0.014 to 0.022 micrometres from band 1 to band 32. In theory, this situation renders the classical wavelet transform inapplicable. Interpolation could be employed to generate a series of equally spaced data points from the unequally-spaced data, but the process of interpolating is a form of low-pass filtering so that the resulting equispaced data is smoothed. An alternative is to ignore the requirement of equal sampling intervals and proceed as if the data were equally spaced (Pensky and Vidakovic 2001). However, this could be dangerous, since treating the irregularly spaced data as if they are regularly spaced introduces additional noise into the data (Press *et al.* 1992).

The key question is: how robust is the method of wavelet de-noising to departures from the assumption of equal sample spacing? If the variation in inter-sample spacing is small – say less than 10% of the ideal (equal) inter-sample spacing - then the additional noise introduced by the use of unequally spaced data could be considerably less than the sampling variation of the noise variance estimate that is used in wavelet de-noising. If this is the case, then the de-noising method will produce results that are adequate, if not ideal. In the context of smoothing, Press *et al.* (1992) claim that irregular spacing of data points in a series that is being smoothed using a moving window filter will not have a serious impact on the result as long as the noise at a single point multiplied by $\sqrt{N/2}$ (N is the window length) is greater than the change in f over the range of the moving window (f is the spectrum value). This is not directly applicable to wavelet de-noising, but it does indicate that the assumption of equal spacing is not a strict one.

Examination of the DAIS data used in this study shows that 10 out of the 32 data points lie outside the range $\bar{x} \pm r$, where $\bar{x}$ is the mean spacing between spectral bands and r is equal to 10% of the mean value. The noise added by the violation of the equispaced sampling assumption will be measurable (though not easy to estimate) but, given the noisiness of the DAIS spectra, it is unlikely to have a significant effect. In support of this conclusion it should be pointed out that, with a data series of length $n = 32$, the standard error of the noise variance estimate will be large, and the additional noise introduced by the use of unequal sample intervals should be considerably less than the estimation error of the noise variance. The only way to test this conclusion is to observe the results achieved by de-noising based on wavelet shrinkage.

The formal accuracy assessment on the 'hard' classification result has not yet been performed, but the classified first derivative map appears to be reasonably accurate and close to what the authors observed during the fieldwork. The limitation on the use of the hyperspectral bands, due to the very high susceptibility of the data to striping after band 32, could result in difficulties in the extraction of more information from the hyperspectral data. However, investigation of the result suggests that, even with the limited number of bands used in the classification, the result is still acceptably good. This also could suggest the possibility of using derivative features as a feature reduction tool.

The problem associated with the characteristics of the sensor, such as the scanning mechanism that results in the susceptibility to striping, could limit the effectiveness of derivative analysis. A higher sensor quality might permit less problematic use of derivative analysis. Another problem in the use of the technique is the selection of the so-called 'mother wavelet' which, in effect, defines the high and low pass filter coefficients that are used in the hierarchical decomposition. There are a number of options. It is difficult to find any practical advice on which one should be used. The fixing of a universal value for the threshold to be used in de-noising is also open to subjectivity. Nevertheless, the combination of the use of derivative spectra and wavelet de-noising appears to be an effective way of processing hyperspectral imagery.

5 CONCLUSIONS

Derivative technique provides an alternative way in the analysis of hyperspectral data besides the straightforward use of original reflectance data. However, the advantages of using derivative analysis can be seriously hampered by the sensitivity of the technique to noise in the data. The wavelet-based de-noising technique is shown to be as an effective way to deal with noisy signals normally encountered in remote sensing data. This preliminary study suggests that the combination of derivative and wavelet-based de-noising techniques is feasible for analysis and mapping using hyperspectral data. It has been shown that the derivative spectra or image from de-noised data can be interpreted more easily than the derivatives of the raw data.

The research on the use of wavelets in hyperspectral remote sensing is still very limited and many opportunities are open for future investigation. Future work will include further investigation of the robustness of wavelet de-noising to unequally spaced data points, and the use of the de-noised derivative spectra in a stepwise unmixing method that will be extendable to coarser resolution data such as Landsat ETM+ (which, unlike the DAIS hyperspectral data, is acquired on a regular basis and is therefore suitable for monitoring temporal change in this important and vulnerable area). The use of two-dimensional wavelet transforms for de-noising two-dimensional signal (e.g. raster images) is also feasible and will be the next step in the research.

ACKNOWLEDGEMENTS

The authors express their gratitude to Professor José Gumuzzio of the Autonomous University of Madrid, Spain for the provision of the DAIS 7915 hyperspectral data, and to German Aerospace Centre (DLR) for the efficient pre-processing of the data. Thanks also to Thomas Schmid, Magaly Koch, and Mahesh

Pal for their help with fieldwork in La Mancha. Mr. Helmi's research is supported by a Universiti Putra Malaysia (UPM)-Malaysian Government scholarship.

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