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Consideration of smoothing techniques for hyperspectral remote sensing

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Abstract

Spectral smoothing filters are popularly used in a large number of modern hyperspectral remote sensing studies for removing noise from the data. However, most of these studies subjectively apply ad hoc measures to select filter types and their parameters. We argue that this subjectively minded approach is not appropriate for choosing smoothing methods for hyperspectral applications. In our case study, it is proved that smoothing filters can cause undesirable changes to statistical characteristics of the spectral data; thereby, affecting the results of the analyses that are based on statistical class models. If preserving statistical properties of the original hyperspectral data is desired, smoothing filters should then be used, if necessary, after careful consideration of which smoothing techniques will minimize disturbances to the statistical properties of the original data. A comparative *t*-test is proposed as a method for choosing a smoothing filter suitable for hyperspectral data at hand.

Keywords: Aggregation; Convolution; Hyperspectral; Optimization; Savitzky–Golay; Moving average; Spectral smoothing filters

1. Introduction

One of the most important problems of using hyperspectral data is signal noise levels. It is normally found that the noise level in hyperspectral data is high as their narrow bandwidth can only capture very little energy that may be overcome by the self-generated noise inside the sensors. Additionally, physical disturbances such as the fluctuation of light illumination and atmospheric states make the situation worse as the disturbances decrease the precision of spectral signals recorded by the sensor (Oppenheim and Schafer, 1975; Landgrebe, 1997; Lyon, 2004).

Spectral smoothing and aggregating techniques including both linear and non-linear methods are popularly used in a large number of modern hyperspectral remote sensing studies for removing noise from the spectral data (Chen et al., 2001; Ben-Dor et al., 2002; Andréfouët et al., 2003; Vaughan et al., 2003; Rees et al., 2004; Smith et al., 2004; Thenkabail et al., 2004; Whiting et al., 2004; Zhang et al., 2004; Wu et al., 2005). However, most of these studies subjectively apply ad hoc inspections as their measure to select appropriate smoothing methods. In other words, they do not use any strict optimizing criteria to select suitable smoothing filters for their studies.

Smoothing methods cause changes to the original spectral data that could lead to incorrect results in subsequent analyses (Savitzky and Golay, 1964; Kawata and Minami, 1984; Tsai and Philpot, 1998; Gong et al., 2001; Schmidt and Skidmore, 2004). For example, image processing of remotely sensed imagery for accurate plant biophysical studies (Bruce and Li, 2001; Zarco-Tejada et al., 2001; Imanishi et al., 2004;

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Le Maire et al., 2004; Meroni et al., 2004) and vegetation discrimination and classification (Tsai and Philpot, 2002; Hochberg and Atkinson, 2003; Foody et al., 2004; Schmidt et al., 2004) are dependent upon statistical estimates of spectral data that are often dampened by smoothing filters (Fig. 1). Instead, a more objective approach should be proposed as a measure to select the correct smoothing method for a particular hyperspectral application so as to minimize disturbance to the original spectral data.

As a result, there are two major goals in this study. First, this study intends to demonstrate the effects of smoothing techniques on the statistical properties of the spectral response. Second, as a replacement for ad hoc measures, the study aims to propose the use of one statistical test (a pair t-test) as a tool for realizing the trade-off between the choice of smoothing methods and their effects on statistical properties of the original data. A real-world example of plant reflectance responses is used for supporting the argument of this study.

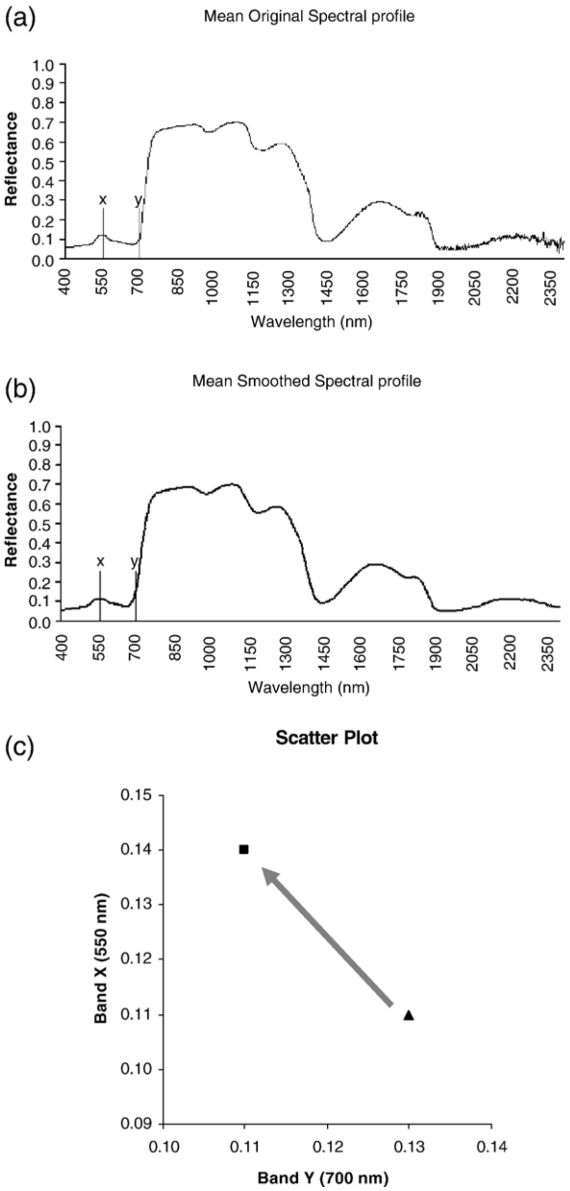

Fig. 1. (a) An average spectral profile of plants before smoothing; (b) an average spectral profile after smoothing; and (c) a scatter plot of the two principal wavelengths (550 and 700 nm) before (triangle) and after (square) smoothing.

2. Methods

2.1. Smoothing techniques

In the field of digital signal processing, the definition of a spectrum $s_o(\lambda)$ observed by a spectrometer is given by the sum of the true signal of the spectrum $s_t(\lambda)$ and the noise $n(\lambda)$ where λ indicates wavelength.

$$s_o(\lambda) = s_t(\lambda) + n(\lambda) \tag{1}$$

Thus, the definition of spectral smoothing is the estimation of $s_t(\lambda)$ from the observed spectrum $s_o(\lambda)$. An estimate $\hat{s}_t(\lambda)$ can be calculated by the convolution of the observed spectrum $s_o(\lambda)$ with a weighting function (i.e. smoothing filter) $g(\lambda)$ chosen by the practitioner:

$$s_t(\lambda) = s_o(\lambda)*g(\lambda). \tag{2}$$

The operator * denotes convolution integral (Oppenheim and Schafer, 1975; Lyon, 2004). There are many types of smoothing filters $g(\lambda)$ adopted by remote sensing practitioners for hyperspectral applications including linear and non-linear methods (Savitzky and Golay, 1964; Kawata and Minami, 1984; Tsai and Philpot, 1998; Foody et al., 2004; Schmidt and Skidmore, 2004). The most popularly used smoothing filters are moving average and Savitzky–Golay filters. Hence, both are selected for this study.

2.1.1. Moving average

The moving average method for smoothing is well-known and has been called by different names, such as running mean and mean average filter. The concept of the moving average filter is simple as it takes the mean spectral value of all points within a specified window (i.e., filter size) as the new value of the middle point of the window (Tsai and Philpot, 1998). The method is solely based on linear calculations and has one key parameter, the filter size.

2.1.2. Savitzky–Golay

The concept of this method is based on simple polynomial least-square calculations. However, instead of fitting a least-square curve to the total length of spectrum at once, the method fits the spectral data piece-by-piece with the size equal to a user-defined value (i.e., filter size) using a special form of matrix calculations (Savitzky and Golay, 1964; Steinier et al., 1972; Madden, 1978). This method requires two key parameters: the filter size and the degree of polynomial orders.

2.2. Hyperspectral data collection

The data used for testing the key hypothesis of this study are laboratory spectra of mangrove leaves. The data were recorded from the leaves of 16 tropical mangrove species listed in Table 1. The leaves were collected using a line-transect method from mangrove trees (higher than 2.5 m) in the natural mangrove forest of Ao Sawi (Sawi Bay), Chumporn province, the south of Thailand (10° 15′N, 99° 7′E). There were ten transects randomly placed throughout the area so as to collect tree samples from every mangrove zone (e.g., pioneer, intermediate, and upper zones). Leaves were picked off the trees just before the spectral measurement in order to preserve the original leaf quality. Specifically, on 6 February 2001, a few major branches of every randomly sampled tree were cut off and transported to the laboratory where the leaves were picked for spectral measurements.

Freshly picked leaves were randomly divided into 30 piles of the same size (20 to 30 leaves) per mangrove species. First, each pile of leaves was randomly spread on top of a black metal plate painted with ultra-flat black paint until the background metal plate could not be seen. Second, we recorded spectral responses of each leaf plate for 20 times. Each plate was rotated 45° horizontally after every fifth record in order to correct for the bi-directional reflectance distribution function (BRDF). Third, the 20 records were averaged to construct a radiance curve. Fourth, the radiance was converted to a reflectance curve, using a spectralon reference panel, as well as the correction of the spectrometer internal current (dark current). We repeated the steps above for all the leaf plates. As a result, 30 reflectance curves were constructed for each mangrove species (Table 1). It should be noted that the whole operation was conducted under a laboratory condition (i.e., dark room, 25 °C) in order to avoid ambient light sources unrelated to the true spectral signal of the leaves.

Table 1
Thirty spectral reflectance curves were recorded per each mangrove species listed below

Mangrove species
1. *Avicennia alba*
2. *Acrostichum aureum*
3. *Bruguiera cylindrica*
4. *Bruguiera gymnorrhiza*
5. *Bruguiera parviflora*
6. *Ceriops tagal*
7. *Excoecaria agallocha*
8. *Heritiera littoralis*
9. *Lumnitzera littorea*
10. *Lumnitzera racemosa*
11. *Nypa fruticans*
12. *Pluchea indica*
13. *Rhizophora apiculata*
14. *Rhizophora mucronata*
15. *Sonneratia ovata*
16. *Xylocarpus granatum*

The FieldSpec Pro FR spectroradiometer (Analytical Spectral Device, Inc.) was equipped with three spectrometers (i.e., VNIR, SWIR1, and SWIR2), covering 350 to 2500 nm (2151 bands in total), with sampling intervals of 1.4 nm between 350 and 1000 nm, and 2 nm between 1000 and 2500 nm. The spectral resolution of the spectrometers was 3 nm for the wavelength interval 350 to 1000 nm, and 10 nm for the wavelength interval 1000 to 2500 nm. The sensor, equipped with a field of view of 25°, was mounted on a tripod and positioned 0.5 m above the leaf plate at the nadir position. A halogen lamp fixed at the same position was used to illuminate the sample plate.

2.3. Experimental use of smoothing filters

2.3.1. Statistical comparisons

We smoothed all the leaf spectra of the mangrove species listed in Table 1 (N=480 spectra in total) using two different types of smoothing filters: (i) moving average and (ii) 2nd order Savitzky–Golay. Filter sizes in use were exhaustively varied between 7 and 51 with the increment of 2 (i.e., i=7, 9, 11,..., 51) for each filter type. Then, we statistically compared the smoothed data against the original spectral data using pair t-tests for all the filters. The test was thoroughly conducted at every spectral location between 400 and 2400 nm. In other words, for each filter, H_o: $\mu_s(\lambda)-\mu_o(\lambda)=0$ and H_a: $\mu_s(\lambda)-\mu_o(\lambda)\neq 0$ where $\mu_s(\lambda)$ is the mean of smoothed spectra at λ nm wavelength (λ=400,...,2400 nm) and $\mu_o(\lambda)$ is the mean of original spectra at the same wavelength.

2.3.2. Spectral separability analysis

The effect of smoothing on the original data was quantified using a spectral separability index. The

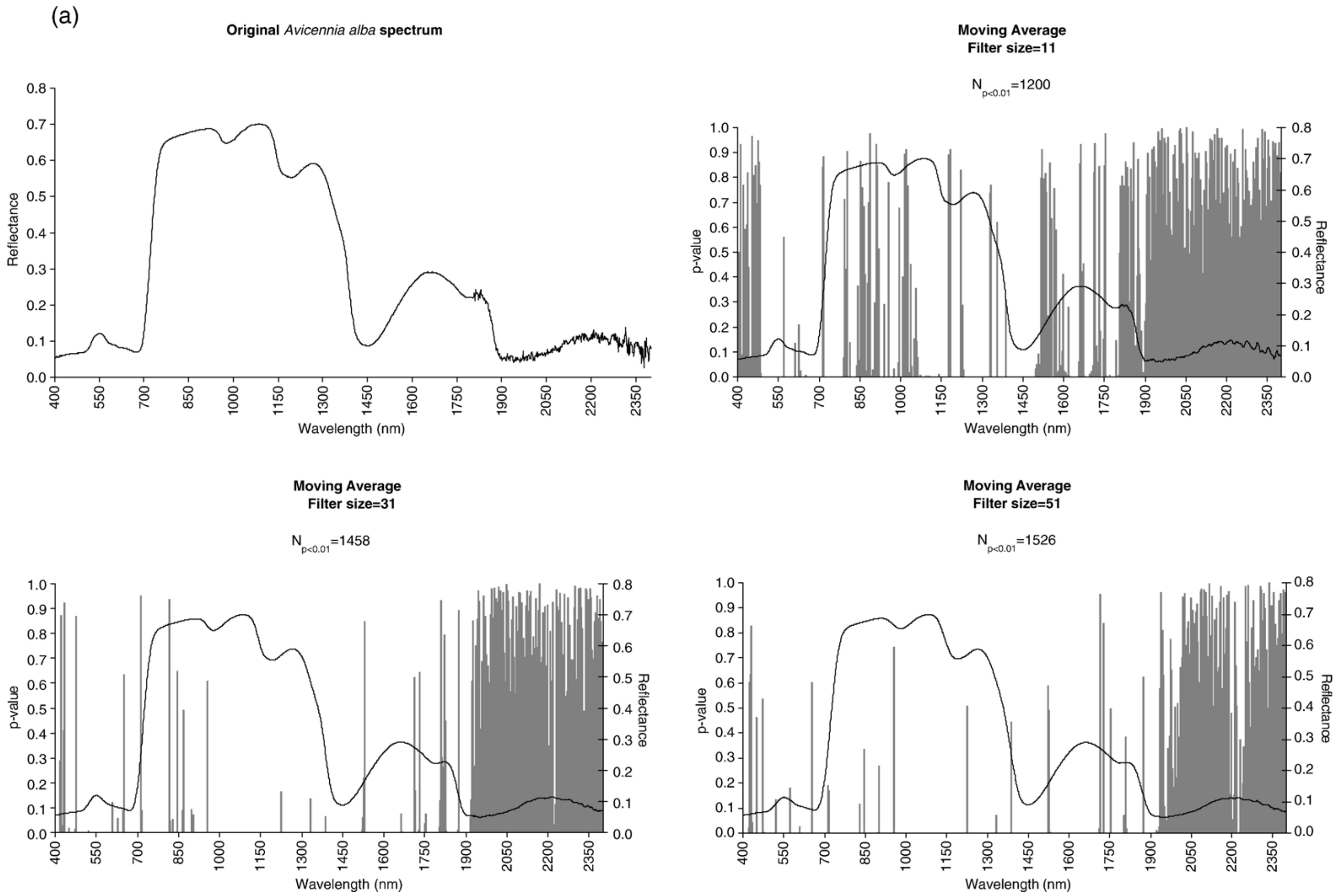

Fig. 2. The effect of smoothing filters on the mean of the leaf-level spectral data of 16 mangrove species: (a) moving average filters; and (b) 2nd order Savitzky–Golay filters.

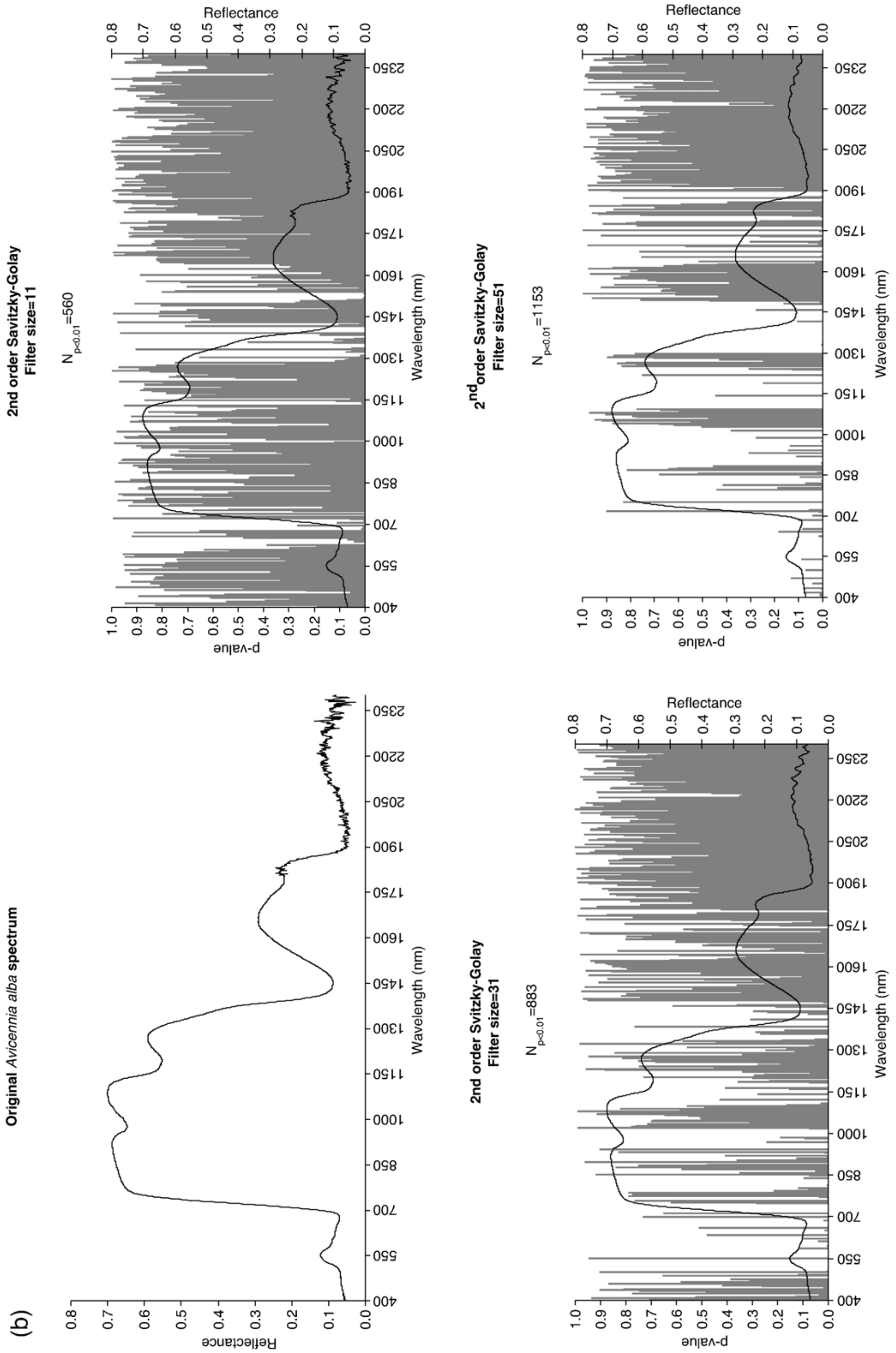

Fig. 2 (continued).

separability index used in this study was the square of Jeffries–Matusita (J–M) distance analysis. The J–M distance method delivers a value between 0 and √2 (≈1.414), so the squared distance gives a number between 0 and 2. The calculation of the J–M distance in this study was based on the following equation (Eq. (3)). See Richards (1993) for further details in separability analyses.

$$\mathrm{JM}_{ij} = \sqrt{2(1-e^{-a})} \text{ where}$$
$$a = \frac{1}{8}(\boldsymbol{\mu}_i - \boldsymbol{\mu}_j)^{\mathrm{T}}\left(\frac{\mathbf{C}_i + \mathbf{C}_j}{2}\right)^{-1}(\boldsymbol{\mu}_i - \boldsymbol{\mu}_j) + \frac{1}{2}\ln\left(\frac{\frac{1}{2}|C_i + C_j|}{\sqrt{|C_i| \times |C_j|}}\right). \tag{3}$$

Note: i and j are the spectral responses of two classes being compared. $\mathbf{C}$ is the covariance matrix of the spectral response, $\boldsymbol{\mu}$ is the mean vector of the spectral response, ln is the natural logarithm function, T is the transposition function and $|C|$ is the determinant of $\mathbf{C}$.

The J–M distance index was used for quantifying spectral separability between two very similar mangrove classes, *R. apiculata* and *R. mucronata*, to see whether smoothing reduced separability between the two classes. Due to “the curse of dimensionality” (Bellman, 1961; Hughes, 1968; Fukunaga, 1990), a subset of the whole range of all spectral bands had to be chosen prior to the separability analysis. Thus, spectral bands used for calculating the J–M distance were: 513, 717, 1263, 1385, 1489 and 1669 nm. These principal spectral locations were selected by a feature selection algorithm (please see further details of the algorithm in Siedlecki and Sklansky, 1989; Kavzoglu and Mather, 2002; Yu et al., 2002; Vaiphasa, 2003).

3. Results

Each small plot in Fig. 2 demonstrates the p-values of the comparative t-tests between smoothed and original data for all spectral locations between 400 and 2400 nm. In brief, if a p-value at a particular spectral location was as low as 0.01, it demonstrated that the smoothed data were statistically different from the original spectral response with 99% confidence. This illustrated that the original spectra were significantly disturbed by the chosen smoothing method. For example, the 2nd order Savitzky–Golay filter at size 11 resulted in 560 statistically disturbed bands ($N_{p<0.01}=560$). Additionally, original and smoothed spectral curves of *Avicennia alba* were also included in the figure so as to illustrate the smoothing effect of each filter.

It is important to note that, even if we have exhaustively done the t-test for 2 filter types with sizes between 7 and 51, we only illustrated in Fig. 2 the results of the 2 filters at 3 different sizes, including 11, 31, and 51 for the purpose of brevity. Instead, the results of the exhaustive experiment for all filter types and sizes were summarized in Fig. 3. The plot demonstrated the number of statistically different spectral locations with 99% confidence ($N_{p<0.01}$) per filter size. Overall, it was found that moving average filters statistically disturbed the original spectral response more than Savitzky–Golay filters as the number of statistically different locations steadily increased from 1000 to 1526. In contrast, the number of statistically different locations of Savitzky–Golay filters increased from 606 to 1153. The general trends of both moving average and Savitzky–Golay filters indicated that bigger filter sizes resulted in higher statistical disturbances even if there were some exceptions in the trend of Savitzky–Golay filters where local minima were noticeable.

The reader may note that, even if the number of spectral bands that have p-values less than 0.01 ($N_{p<0.01}$) were recorded for every filter, the p-value level at 0.01 were not used as a critical value α for accepting or rejecting the outcome of one individual filter. Instead, the $N_{p<0.01}$ was only used for the purpose of comparisons between the influences of smoothing filters on the spectral mean. In the case that the reader wishes to make a decision to accept or reject the smoothing results of one individual filter on the basis of the reported p-values

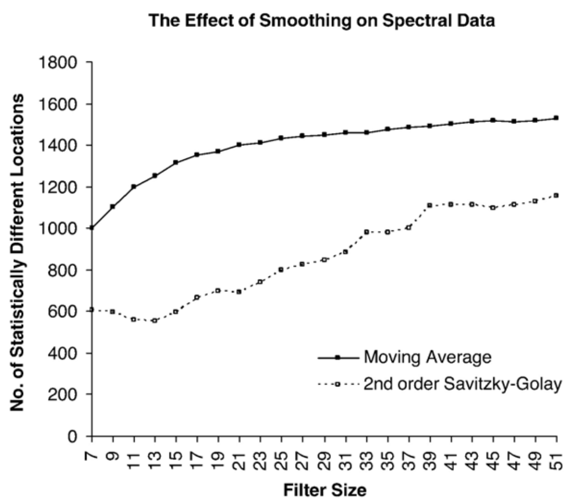

Fig. 3. The number of statistically disturbed locations ($N_{p<0.01}$) caused by moving average and Savitzky–Golay filters.

Table 2
Comparison between J–M distance indices of two very similar mangrove classes, *R. apiculata* and *R. mucronata*, before and after smoothing

Filter type	Filter size	J–M distance
Moving average	11	1.9311
	31	1.9254
	51	1.9163
2nd order Savitzky–Golay	11	1.9314
	31	1.9307
	51	1.9284
Original data	n/a	1.9315

alone, the reader has to adjust α to the effect of "multiplicity" (i.e. increasing chance of having Type I error as the number of tests grows) (Rothman, 1990; Hsu, 1996; Perneger, 1998; Feise, 2002). Nevertheless, such consideration of one individual filter was not the intention of this study.

Finally, the results of the separability analysis between the two mangrove classes (*R. apiculata* and *R. mucronata*) were demonstrated in Table 2. It was found that none of the J–M distance indices of the smoothed data was higher than the J–M distance index of the original data. In other words, spectral smoothing reduced separability between the two mangrove classes. Additionally, the results in Table 2 also reflected the trends in Fig. 3 as the separability index reduced while the filter size increased.

4. Discussion and conclusion

This case study demonstrated that the effects of smoothing on the statistical estimate of spectral data were likely to negatively affect the outcome of subsequent analyses that utilized statistical characteristics of the spectral data. This problem was evident in Table 2 as smoothing filters reduced separability between the two mangrove classes, *R. apiculata* and *R. mucronata*. This outcome demonstrated that spectral smoothing may not enhance the data but made it more difficult to separate the two mangrove classes in the spectral feature space. This argument also may be true for the following spectral discrimination and classification studies that used ad hoc measures to select smoothing filters without preserving statistical properties of the original data (Gong et al., 2001; Andréfouët et al., 2003; Hochberg and Atkinson, 2003; Schmidt and Skidmore, 2003; Vaughan et al., 2003; Yamano et al., 2003; Castro-Esau et al., 2004; Foody et al., 2004; Rees et al., 2004; Schmidt et al., 2004; Thenkabail et al., 2004).

An instructive example of how to use the *t*-test method for choosing smoothing filters can be described as follows. In Fig. 2, if an ad hoc criterion was in use, a practitioner who was challenged to smooth the spectral profile of *A. alba* might face a dilemma to choose between the size-31 moving average filter and the size-51 Savitzky–Golay filter so as to remove the noise in the mid-infrared region of the spectrum (i.e. ≈1900–2400 nm), as well as try not to over-smooth the data. In contrast, when the *t*-test was applied, its results encouraged the practitioner to select the size-51 Savitzky–Golay filter as it possessed fewer statistically disturbed bands (i.e. the $N_{p<0.01}$ of the size-51 Savitzky–Golay filter was 1153 while the $N_{p<0.01}$ of the size-31 moving average filter was 1458).

Even if this case study was based on two most popularly used filters (moving average and Savitzky–Golay), it was anticipated that the *t*-test method was a universal method that can be used for choosing smoothing filters other than moving average and Savitzky–Golay. Moreover, the method is not limited to vegetation spectra. It could be used for other case studies, for example, selecting appropriate smoothing filters for mineral spectra. However, the number of spectral samples required for *t*-statistics (e.g. $N \approx 20$ samples) is one obvious limitation of the method.

In the continuing study, the concept of using statistical measures for constraining the selection of spectral smoothing such as the *t*-test could be expanded to a greater extent. Instead of using only *t*-tests that constrained the disturbance on the statistical mean, *F*-tests could be integrated to limit the disturbance on the statistical variance. In addition, designing smoothing filters that preserved other properties of the original spectral data such as signal strength (i.e., maximizing signal-to-noise ratios) could also be an interesting topic for future research. So far only a few pioneer studies have been found in this area (Kawata and Minami, 1984, Bruce and Li, 2001; Schmidt and Skidmore, 2004).

In conclusion, hyperspectral smoothing should be used, if necessary, with objective justification of which smoothing technique causes minimal damages to the original data in terms of statistical differences. Therefore, we proposed a comparative *t*-test as a measure for choosing the best smoothing filter for the hyperspectral data at hand.

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