Hyperspectral Data for Tropical Mangrove Species Discrimination

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ABSTRACT The aim of this study was to test the performance of hyperspectral data in discriminating mangroves at the species level. First, spectral responses between 350 nm and 2500 nm of 16 Thai tropical mangrove species were recorded from the leaves, using a field spectrometer under laboratory conditions. Next, the mangrove spectra were statistically tested to see whether they significantly differed at every spectral location. Finally, the spectral separability between each pair of mangrove species was quantified using the J-M distance measure. The results demonstrated that the mangrove species were spectrally separable, and we therefore anticipate the use of hyperspectral sensors for mangrove species classification.

1. INTRODUCTION

The limited spectral bands of a traditional sensor such as Landsat TM offer a clear example of how opportunities to exploit spectral responses linked to the physical-chemical properties of plants are lost (Curran, 1989, Elvidge, 1987, 1990, Himmelsbach et al., 1988, Kumar et al., 2001, Williams and Norris, 1987). This problem can be resolved using more delicate methods such as hyperspectral technology. Additionally, there is already a couple of evidence to show that using hyperspectral data helps to improve the study of mangroves at a finer level. Demuro and Chisholm (2003) give a good example of how a hyperspectral sensor (HYPERION) handles the task of discriminating 8-class mangrove communities in Australia - a task considered difficult for any multispectral sensors (Green et al., 2000). Moreover, the AVIRIS sensor performed just as well in mapping the mangrove communities of the Everglades, Florida (Hirano et al., 2003). So far no conclusion has been reached as to whether or not hyperspectral information can be used to study mangroves at the species level (i.e. for species discrimination). Consequently, this study aims to test and quantify the capability of hyperspectral data based on laboratory mangrove spectra recorded from 16 Thai tropical mangrove species.

2. METHODS

2.1 Acquisition of hyperspectral data

2.1.1 Mangrove leaf preparation Mangrove leaves of 16 Thai tropical mangrove species 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, in the south of Thailand (10º 15’N, 99º 7’E). There were ten transects randomly placed throughout the area so as to collect tree samples from every mangrove zones (e.g. pioneer, intermediate, and upper zones). The leaves were picked off the trees just before 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, and the following day the leaves were picked for spectral measurement.

2.1.2 Leaf spectral measurements The freshly picked leaves of each species were randomly divided into 30 piles of the same size (20 to 30 leaves). For each spectral measurement, each pile of leaves was spread on top of a black metal plate painted with ultra-flat black paint until the background metal plate could not be seen. Each measurement was performed under laboratory conditions (i.e. dark room, 25ºC) in order to avoid ambient light sources unrelated to the true spectral signal of the leaves. As a result, 30 spectra were measured for each mangrove species (Table 1).

Each measurement was conducted using a FieldSpec® Pro FR spectroradiometer (Analytical Spectral Device, Inc.). This spectroradiometer is equipped with three spectrometers (i.e. VNIR, SWIR1, and SWIR2), covering 350 nm to 2500 nm, with sampling intervals of 1.4 nm between 350 nm and 1050 nm, and 2 nm between 1000 nm and 2500 nm. The spectral resolution of the spectrometers was 3 nm for the wavelength interval 350 nm to 1000 nm, and 10 nm for the wavelength interval 1000 nm 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. The bi-directional reflectance distribution function (BRDF) of each sample is corrected by rotation method. The radiance was converted to reflectance, using a spectralon reference panel for every measurement as well as the correction of the spectrometer internal current (dark current).

2.2 Experimental setup

2.2.1 Statistical test First of all, we tested whether the mangrove spectra of the 16 species (Table 1) were statistically different at every spectral band, that is to say, the null hypothesis Ho: $\mu_1=\mu_2=\cdots=\mu_{16}$ versus the alternative hypothesis Ha: $\mu_1\neq\mu_2\neq\cdots\neq\mu_{16}$, where μ_i was the mean reflectance value of the i^{th} species (i.e. i = 1, 2,…, 16). The test was carried out using one-way ANOVA at every spectral location between 350 nm and 2500 nm (a total of 2151 spectral bands) with a 95% confidence limit (α=0.05).

2.2.2 Spectral separability Although the statistical test demonstrated whether the mangrove species were significantly different or not at the spectral locations, it could not quantify the likelihood of each pair of the mangrove species being spectrally separated from one another. This pair-wise information is necessary for a detailed investigation of species separability. Therefore, we applied the J-M distance measure to quantify this for each mangrove pair. The distance measure reported a separability value between 0 and 2 for every mangrove pair. The pairs that possessed a value close to 2 were highly separable, and vice versa. Details of the distance measure are given by Richards (1994).

Because the J-M distance measure is a parametric method, it was necessary to reduce the number of spectral features (bands) prior to the calculation. It was not possible to calculate the J-M distance using all 2151 bands because of the singularity problem of matrix inversion (i.e. the number of spectral samples per mangrove species is too small). In this study, we applied a wrapper feature selection approach (please see John et al., 1994; Kavzoglu and Mather, 2002; Kohavi and John, 1997; Siedlecki and Sklansky, 1989; Vaiphasa, 2003; Yu et al., 2002) to reduce the number of spectral features.

In our experiment, we applied the algorithm to select (i) the best 2-band combination, (ii) the best 3-band combination, (iii) the best 4-band combination, (iv) the best 6-band combination, (v) the best 8-band combination, and (vi) the best 10-band combination out of the total of 2151 bands. For every selection, the algorithm was initialized with the following parameters: crossover rate = 50%, mutation rate = 1%, fitness score threshold = 80%. The maximum number of iterations was 1000.

3. RESULTS

3.1 ANOVA test

Following the null and alternative hypotheses stated in the previous section, the test result (p-values) of every spectral band was illustrated (see Figure 1). A reflectance of *Rhizophora apiculata* measured in the laboratory was also drawn in the plot to give an impression of the actual mangrove spectral continuum collected by the spectrometer. According to the statistical test, the 16 mangrove species under study seemed to be statistically different at most of the spectral locations, with a 95% confidence level (p-value<0.05). The total number of spectral bands that had p-values less than 0.05 was 1941, of which 477 even complied with a 99% confidence level (p-value<0.01). The exceptions were in the ultraviolet region at the left end of the plot, in the shortwave infrared region at the right end, and a few bands of the near-infrared region where the p-values were higher than 0.05.

3.2 Wrapper feature selection

The objective of this section is to reduce the number of bands prior to the distance analysis in the next section. We applied the feature selection algorithm to search for the best spectral band combinations out of the total of 2151 bands. The real-time performances of six different sizes of band combination are shown in Figure 2. The vertical axis represents the average fitness score or the information about class separability (i.e. estimated classification accuracy), ranging from 0% to 100%. The horizontal axis is the number of iterations. At the beginning, the average fitness scores of the six experiments increased dramatically, and then leveled off at about the 40th iteration. Only the band combinations with a number of members greater than four could successfully pass the fitness threshold level (i.e. 80% classification accuracy). In contrast, the band combination with three members struggled to stay above the threshold level (i.e. it fluctuated above and below the threshold line) because the spectral information of three bands was not enough to resolve the difference between 16 mangrove species. For the same reason, the band combination with only two members could achieve nothing better than a 50% fitness score. After running the algorithm for 1000 iterations, the bands were successfully selected for each experiment, and these are shown in Figure 3.

We note that in all cases the experiments selected at least one spectral band from the red edge area (the steep spectral slope between band 331 and band 410). The second most common spectral feature selected by most of the experiments was at another steep slope between band 950 and band 1090 (infrared edge). Disagreements might be noticed between the statistical test (Figure 1) and the band selection (Figure 3), as two bands (one from Figure 3(iv), the other from Figure 3(vi)) were selected from the noisy region at the right end of the mangrove spectral reflectance, which would not give any useful spectral information. However, we found that both of them possessed p-values lower than 0.05.

According to the 80% fitness threshold, we considered that the performance of the best four bands (Figure 3(iii)) was the most computationally efficient, as it satisfied the selected fitness threshold with a lower number of selected bands. As a result, we used the four selected bands for the experiment in the next section. The best four were band 371 (720 nm), band 928 (1277 nm), band 1066 (1415 nm), and band 1295 (1644 nm).

3.3 J-M distance

We applied the J-M distance measure to reveal the spectral separability between each pair of mangrove species (Table 2), using the four spectral bands selected in section 3.2. The distance measure reported a number between 0 and 2 for every species pair, in which 0 was the lowest level of separability and 2 was the highest. The overall spectral separability between the pairs of mangrove species seemed high, since most of them acquired a level of separability higher than 1.90. Instances where the distance was lower than the 1.90 separability level are highlighted in Table 2.

4. DISCUSSION

Despite omitting the important issue of spatial resolution from this study, we anticipate that hyperspectral data, which can now be acquired from many airborne sensors and hyperspectral satellites, can be used for discriminating mangroves at the species level. The results of the ANOVA hypothesis test (Figure 2) and the J-M distance analysis (Table 2) provide strong supporting evidence to this effect.

It is very likely that the ultraviolet region possessed relatively high p-values because our laboratory measurements relied on an artificial light source (halogen lamp) that radiated a negligible amount of ultraviolet energy, and consequently the signal-to-noise (S/N) ratio of the ultraviolet range was relatively low. Therefore, the region did not contain any meaningful plant information but the noise. Like the ultraviolet region, the p-values of the shortwave infrared region on the right also suffered from the S/N ratio, because the incandescent lamp in use did not strongly radiate the energy in this region. On the other hand, the weakness of the light source caused no deterioration in the p-values of the bands in the near-infrared region. Instead, the difficulty in discriminating mangroves when using near-infrared spectral information was probably caused by a characteristic of plants in general: they have little absorption on the electromagnetic wave of this region (Kumar et al., 2001). Thus, light reflection and transmission from mangrove leaves are the two dominating factors of the near-infrared spectral response. These two factors are controlled by the internal structure of the leaves (Gates, 1965; Sinclair et al., 1971), which is quite similar across mangrove species (Tomlinson, 1994).

The J-M distance analysis (Table 2) reveals the spectral distance between every pair of mangrove species. In general, the result convinces us that the species are highly separable, as most of the mangrove pairs possess a spectral distance higher than 1.90. There are only some pairs that possess slightly lower spectral distances (highlighted in Table 2). Among the highlighted pairs, the lowest distance score of 1.56 between *Acrostichum aureum* (coded 2) and *Bruguiera gymnorrhiza* (coded 4) surprised us most, because the former is a type of understorey plant whereas the latter belongs to the Rhizophoraceae family. It seems that both plants are likely to share similar leaf biophysical properties.

The singularity problem during matrix inversion made it impossible to use all 2151 spectral bands for the calculation of the J-M distance. Thus, we had to apply the wrapper feature selection algorithm prior to the calculation. The result showed that only four bands were necessary for guaranteeing the class separability of the 16 mangrove species: 720 nm, 1277 nm, 1415 nm, and 1644 nm. The four bands selected, however, cannot for the most part be reconciled with the locations of the spectral responses of mangrove leaf pigments (chlorophylls and carotenoids) found in the literature (Das et al., 2002). This could lead us to hypothesize that the spectral responses of these pigments, which are situated at a relatively short wavelength between 380 nm and 750 nm, may be less important spectral information for mangrove species discrimination than the information from the spectral responses of the other leaf components that interact with light energy at longer wavelengths. This may be because mangroves generally possess similar amounts of pigment substances across the species, and the differences in other leaf components, such as sugar, water, protein, oil, lignin, starch, and cellulose, that normally interact with light at longer wavelengths (Kumar et al., 2001) are more marked.

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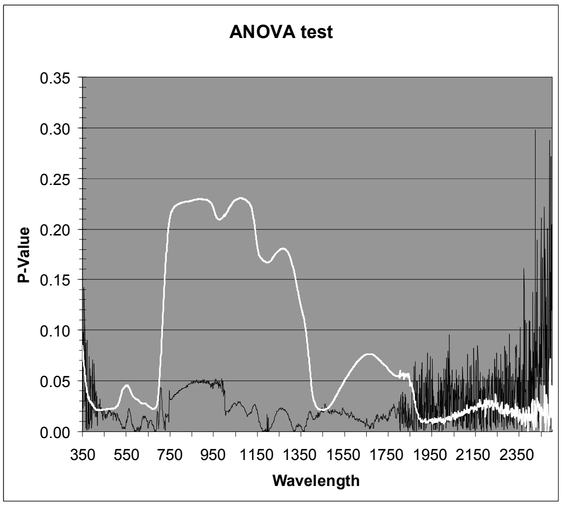


Figure 1: The result of the ANOVA test (black line) showing against a laboratory reflectance of *Rhizophora apiculata* (white line)

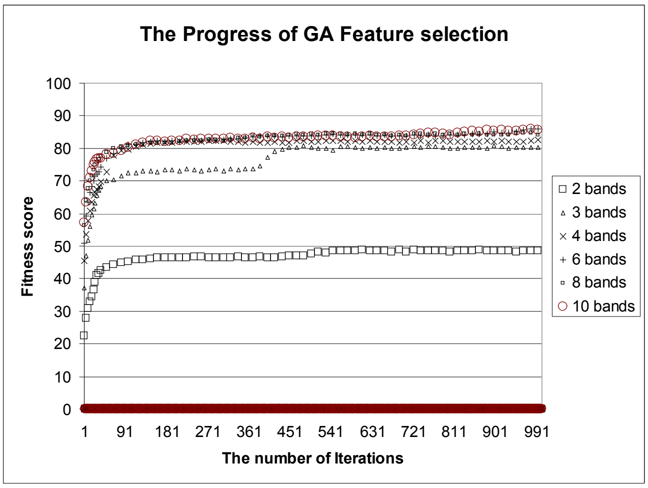


Figure 2: Real-time performance of the wrapper feature selection for 1000 iterations

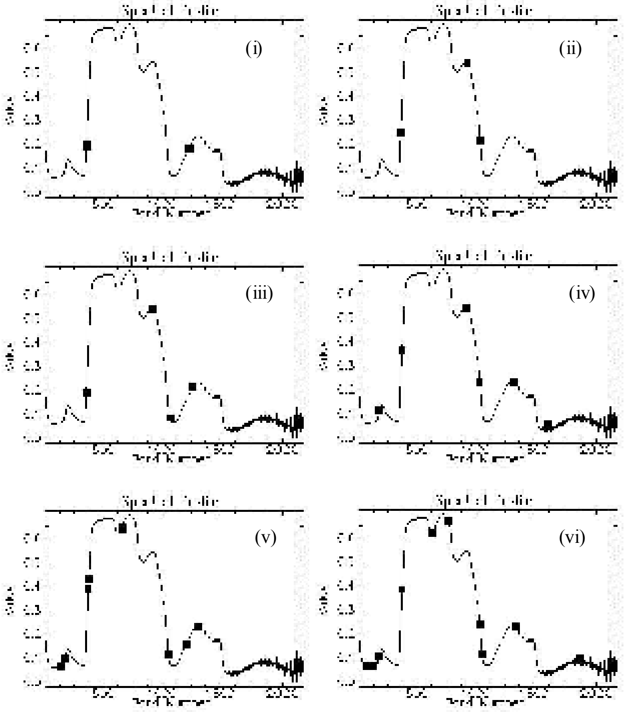
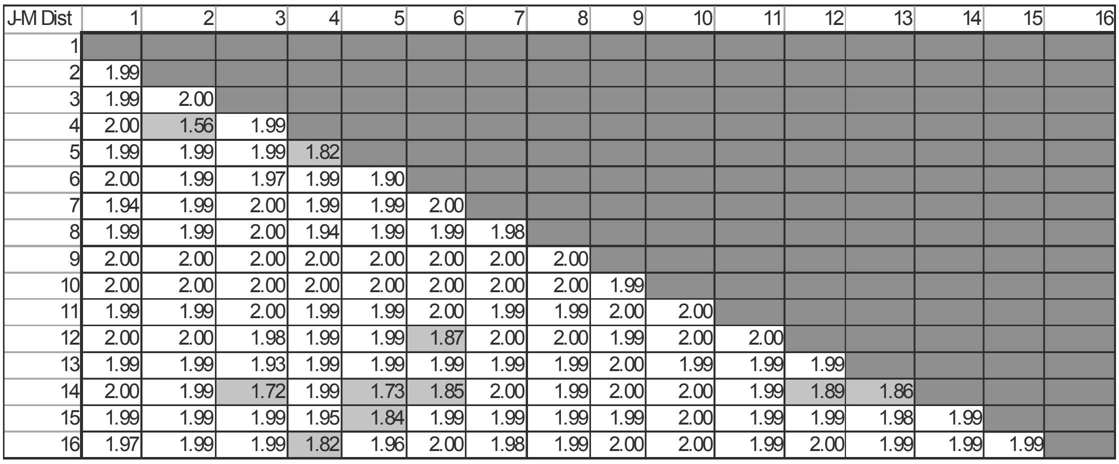


Figure 3: The locations of spectral bands selected by the feature selection tool: (i) the best 2-band, (ii) the best 3-band, (iii) the best 4-band, (iv) the best 6-band, (v) the best 8-band, and (vi) the best 10-band combinations

Mangrove species	Species code	Number of spectra
Avicennia alba	1	30
Acrostichum aureum	2	30
Bruguiera cylindrica	3	30
Bruguiera gymnorrhiza	4	30
Bruguiera parviflora	5	30
Ceriops tagal	6	30
Excoecaria agallocha	7	30
Heritiera littoralis	8	30
Lumnitzera littorea	9	30
Lumnitzera racemosa	10	30
Nypa fruticans	11	30
Pluchea indica	12	30
Rhizophora apiculata	13	30
Rhizophora mucronata	14	30
Sonneratia ovata	15	30
Xylocarpus granatum	16	30

Table 1 (Left): Thirty spectra of mangrove leaves were collected per mangrove species, using a spectroradiometer

Table 2 (Below): The J-M distances between the pairs of 16 mangrove species were calculated using the four bands selected in section 3.2. The pairs that possess a separability level lower than 1.90 are highlighted.



J-M Dist	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1																
2	1.99															
3	1.99	2.00														
4	2.00	1.56	1.99													
5	1.99	1.99	1.99	1.82												
6	2.00	1.99	1.97	1.99	1.90											
7	1.94	1.99	2.00	1.99	1.99	2.00										
8	1.99	1.99	2.00	1.94	1.99	1.99	1.98									
9	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00								
10	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.99							
11	1.99	1.99	2.00	1.99	1.99	2.00	1.99	1.99	2.00	2.00						
12	2.00	2.00	1.98	1.99	1.99	1.87	2.00	2.00	1.99	2.00	2.00					
13	1.99	1.99	1.93	1.99	1.99	1.99	1.99	1.99	2.00	1.99	1.99	1.99				
14	2.00	1.99	1.72	1.99	1.73	1.85	2.00	1.99	2.00	2.00	1.99	1.89	1.86			
15	1.99	1.99	1.99	1.95	1.84	1.99	1.99	1.99	1.99	2.00	1.99	1.99	1.98	1.99		
16	1.97	1.99	1.99	1.82	1.96	2.00	1.98	1.99	2.00	2.00	1.99	2.00	1.99	1.99	1.99	