Combining Texture and Hyperspectral Information for the Classification of Tree Species in Australian Savanna Woodlands

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Abstract This paper outlines research undertaken to assess the ability of textural information, from image filters, to be used alongside hyperspectral data for the classification of broad forest types. The study made use of 2.6 m hyperspectral HyMap data acquired over the Injune study area, Queensland, Australia, in September 2000. The HyMap data provided spectral data from the blue to shortwave infrared in 126 wavelengths, all of which were used for classification. A measure of texture was achieved using a set of 48 image filters including Laplacian of Guassian and Gaussian smoothing, first and second order derivatives at different scale and where appropriate different rotations. Analysis took place using an air photo interpretation to provide regions of interest for areas dominated by *Angophora*, *Callitris*, and *Eucalyptus*, additionally areas of non-forest were also included. Classification of the resulting dataset was performed using Multiple Stepwise Discriminant Analysis where an accuracy of 60% was achieved using the combined reflectance and texture data compared to accuracies of 55 and 43% using only the reflectance and textural datasets, respectively.

Introduction

The delineation of woodlands into regions unique in terms of species and structure composition is important for many applications, including the provision of forest management units (Leckie et al., 2003), indicators of biodiversity (Bock et al., 2005) and the interpretation of other remotely sensed data.

The interpretation of aerial imagery is heavily scale dependent, where at high spatial resolutions interpretation has traditionally required experienced human interpreters and is mostly based on structure, context and texture, rather than spectral qualities (Held et al., 2003). Therefore, a number of studies (Cots-Floch et al., 2007; Buddenbaum et al., 2005; Coburn and Roberts, 2004; Franklin et al., 2000; Kushwaha et al., 1994) have started to introduce textural measures alongside the

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spectral values. Franklin et al., 2000, found the addition of textural information, in the form of homogeneity and entropy calculated through a moving window, increased the overall classification accuracy of forest stand types by 5–12%, providing overall accuracy in the order of 60–65%. While, Kushwaha et al., 1994 demonstrated an increase in classification accuracy from 69 to 80% when classifying stand age and levels of degradation when the textural measures entropy and the inverse difference moment were introduced alongside the spectral data.

Texture is the term used to describe information on the local variability of the image pixel values. Representation of texture can take a number of forms, one of the most common are the so called Haralick features (Haralick, 1979; Haralick et al., 1973) where the statistical properties of the pixels within a moving window are calculated, representing the homogeneity of the surrounding pixels. Although this method has demonstrated some success (e.g., Franklin et al., 2000), the results often vary with scale and application and have, therefore, not been widely adopted within the field of remote sensing where the pixel values (either reflectance or backscatter) have tended to be used in isolation. Another representation of texture is that of filter responses, where through the application of a number of image filters structures within the scene at different scales and rotations are identified and the composite of these filter responses forms the texture signature or texton (Leung and Malik, 2001, Varma, 2004). The texton is identified from the filter responses through a clustering stage (e.g., K-Means; Varma, 2004; He et al., 2008) where the resulting texton can be used for segmentation and classification.

Study Site and Datasets

The study was carried out using remote sensing and field data acquired over a 40×60 km area near the township of Injune (Lat 25° 32′, Long 147° 32′), located within the Southern Brigalow Belt, a biogeographic region of southeast central Queensland, Australia (Fig. 1). These woodlands contain forest communities

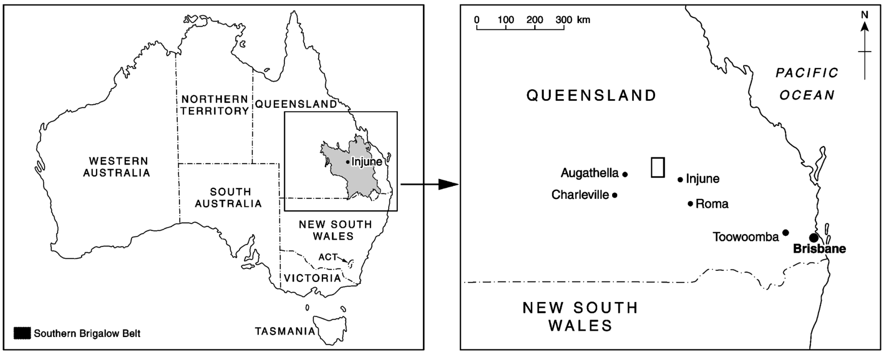

Fig. 1 The location of the Injune study area, southeast central Queensland, Australia. *The shaded area* represents the Southern Brigalow Belt

existing in varying states of degradation and regeneration as a result of prior disturbance (e.g., broad scale clearing, altered fire regimes and spread of exotic species) and are structurally similar to over 70% of those occurring in Australia. Many stands are dominated by *Callitris glaucophylla*, although selective harvesting has reduced the abundance of larger individuals, therefore, typically forming dense stands with a large number of small individuals (several trees per m^2). *Eucalyptus* species are also common across the site with stands dominated by *Eucalyptus populnea* (Poplar Box), *Eucalyptus melanophloia* (Silver-leaved ironbark), *Eucalyptus microcarpa* (Grey Box), *Eucalyptus chloroclada* (Baradine gum), *Angophora leiocarpa* (Smoothed barked apple) and *Angophora floribunda* (Roughed barked apple). Additionally, *Eremophila mitchelli* and a number of *Acacia* species form dense understories. While *Acacia harpophylla* is commonly associated with duplex and cracking clay soils in the southeast of the study area, it is largely in the form of regrowth given previous clearing.

During July 2000, Large Scale (1:4000) stereo aerial photography (LSP) were acquired over a grid of one hundred and fifty 500×150 m Primary Sampling Units (PSUs), with each separated by 4 km in the north-south and east-west directions (Lucas et al., 2004). Across the site, 1 km wide strips of Hyperspectral Mapper (HyMap) data were acquired along six of the PSU columns, at 2.6 m spatial resolution with 126 bands in the VIS, NIR and SWIR parts of the electromagnetic spectrum. The HyMap data were subsequently atmospherically corrected and geo-referenced by HyVista Corporation (who acquired the data) using the HyCorr atmospheric correction software. The algorithm, developed by CSIRO as an extension to the ATREM atmospheric correction software (Gao and Goetz, 1990), retrieves information on atmospheric gases from wavebands operating in the water absorption regions and uses these to correct the image bands.

Methods

Airphoto Interpretation

Using the LSP, an aerial photography interpreter delineated the extent of broad forest communities and described each in terms of the dominant species (Tickle et al., 2006). It was observed that the woodlands were dominated by a number of broad forest communities that were often texturally different as much as they were spectrally different. *Angophora* dominated woodlands were distinct due to the large size of the trees where the textures presented were very course with large areas of ground and shadow being present between the crowns (Fig. 2aa). *Callitris* dominated stands were found to contain relatively smooth textures due to the dense number of stems and homogenous canopy cover (Fig. 2b). While *Eucalypts* (e.g., Silver-leaved Ironbark and Poplar Box) were often found to be only a few pixels (at a pixel resolution of 2.6 m) across but with small areas of soil and shadow visible between the crowns (Fig. 2c).

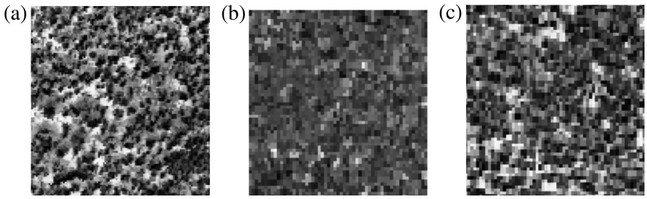

Fig. 2 Examples of the broad forest types (**a**) *Angophora*, (**b**) *Callitris*, and (**c**) *Eucalyptus*

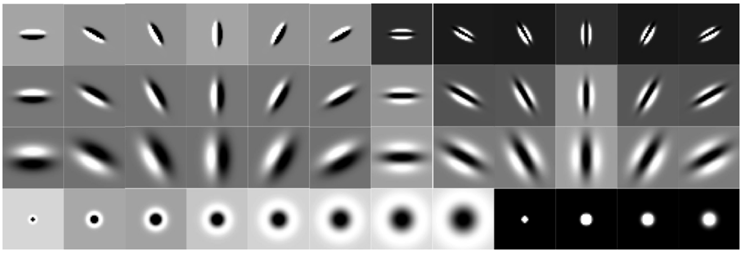

Fig. 3 The filter bank used to identify texture

Image Filtering

To identify the textures within the images a filtering technique similar to that of Varma (2004) was used where a series of image filters (Fig. 3) were applied to the image and the normalised filter responses were used to characterise the texture. For this study the Leung-Malik filter bank (Leung and Malik, 2001), consisting of 48 filters, including 8 Laplacian of Gaussian, 4 Gaussian smoothing filters and 6 Gaussian first and second order derivative filters at 3 scales, was used. For the Laplacian of Gaussian filters scales of $1, \sqrt{2}$, 2, $2\sqrt{2}$, 2, $3\sqrt{2}$, 6 and $6\sqrt{2}$ were used while the Gaussian smoothing used scales of 1, $\sqrt{2}$, 2 and $2\sqrt{2}$. For the Gaussian first and second order derivative filters scales of σ_x, σ_y, (1,3), ($\sqrt{2}$, $3\sqrt{2}$) and (2,6) were used, where each scale was rotated by 0, 30, 60, 90, 120 and 150 degrees.

Remotely Sensed Data and Association to Forest Types

Filtering all 126 wavelengths available from the HyMap sensor would prove impractical due to the data size (48×126 output bands), therefore a subset of 3 bands was selected. The selected bands were in the blue channel (446.1 nm), on the red edge (716.2 nm) and the NIR (891.2 nm). These wavelengths were selected as they have been shown by Bunting and Lucas (2006) to provide the optimum visualisation of these woodlands for the differentiation of tree crowns and species.

Following the application of image filters to each of the image bands the polygons identified from the LSP by the airphoto interpreter were attributed with the mean filter response for each of the 3 input bands along with the mean spectral response for each of the 126 bands.

Classification

Classification was performed on the data extracted for the LSP polygons using Multiple (stepwise) Discriminant Analysis (MDA), from within the SPSS software package. MDA was selected due to its success in the previous studies (Clark et al., 2005, Lucas et al., 2008), where hyperspectral data from individual crowns, from high resolution 1 m imagery, were extracted and classified to species, resulting in accuracies > 70% where 10 species were compared. The algorithm was parameterised such that the stepwise method was applied using the Rao's V metric, with the probability of F being 0.05 for entry and 0.1 for removal of data bands in the forward and backward steps (Galvao et al., 2005).

Results

To test the method the polygons identified through the LSP interpretation for 4 of the 6 HyMap strips were select and attributed with the mean reflectance for each of the HyMap bands and mean filter responses providing 270 variables and 252 samples of the 4 ground cover types (Table 1).

To generate overall accuracy values for the 4 classes each set of samples was randomly split into training and testing datasets, using a Bernoulli distribution with a probability of 0.5. The split was made 25 times where for each split the results of the classification were recorded and the mean and standard deviations calculated. To test the significance of the texture and reflectance data the experiments were carried out individually on the reflectance and texture data as well as the combined data (Table 2).

Table 1 The number of samples for each ground cover type

Species	Number of samples
Angophora (ANG)	10
Callitris (CP-)	82
Eucalyptus (EUC)	130
Non Forest (NF)	30

Table 2 Results for the experiments using both the datasets individual and in combination

	Combined		Reflectance only		Texture only	
	Training	Testing	Training	Testing	Training	Testing
Mean	61.79	60.21	60.98	55.31	50.18	43.31
Std Dev	0.67	0.86	1.10	1.04	1.74	1.51

The results show a modest, 5%, improvement for the testing datasets when the combined data was used over the reflectance data while a significant, 17%, increase from the results using only the texture data. Also, by combining the reflectance and textural data the standard deviation of the classification results have been reduced, demonstrating a more robust classification, less sensitive to the training and testing samples used.

Discussion

From these initial results it is clear that the introduction of textural information has increased the classification accuracy and robustness to a similar extent as previous studies (e.g., Coburn and Roberts, 2004 and Franklin et al., 2000). The use of textural information at this scale is viewed as an important additional (Held et al., 2003) as it more closely corresponds with the methods used by human interpreters and allows the forestry environment to be more fully understood at this resolution. Alternative methods (Bunting and Lucas, 2009) have concentrated on the aggregation of high-resolution results, for example delineated tree crowns classified to species. These methods provide an advantage in that the resulting classification can be attributed with information from high-resolution analysis (e.g., crown area, number of individuals) useful for estimating attributes such as biomass and indicators of biodiversity (e.g., Shannon or Simpson indexes) but require significant effort in the production of intermediate data products to allow the analysis to take place. While the method outlined in this paper and those following on from this method, allow the regions to be directly selected from the imagery without intermediate products.

Limitations of the work mainly centered around the testing and training dataset, derived from the LSP, as although providing a good overview of the study area to guide further remote sensing acquisitions and field surveys, as originally intended, they do not accurately delineate the forest types leading to noise in the training and testing data. Additionally, the low number of *Angophora* samples has limited the reliability of the classification for this forest type which occurs in many parts of the imagery, although often outside the areas for which the LSP data was available, forms a very texturally distinct forest type. Therefore, further samples and more forest types (e.g., *Acacia*) and forest structures (e.g., regrowth, burnt) are to be selected for future study.

Future work on the algorithm will concentrate on data reduction methods to reduce the complexity of the input data, while allowing further variables (e.g., max response, min response and standard deviation) to be used alongside the mean filter responses. In addition, further classification methods (e.g., K-Means clustering, K-Nearest Neighbor and support vector machines) will be investigated with the possibility of further increasing the classification accuracy.

Conclusions

This research has demonstrated the use of a filter based texture measure in addition to spectral data for the classification of forest structural types from the 2.6 m HyMap data where the addition of the textural information contributed to a 5% increase in overall accuracy and robustness of the selected samples. Moving forward this study recommends the use of textural measures alongside reflectance data for studies of this type where large regions (> 1000 pixels) with significant spectral variation are of interest.

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