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Mixed Pixel Analysis for Flood Mapping Using Extended Support Vector Machine

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***Abstract*— This paper addresses the challenges of flood mapping using multispectral images. Quantitative flood mapping is critical for flood damage assessment and management. Remote sensing images obtained from various satellite or airborne sensors provide valuable data for this application, from which the information on the extent of flood can be extracted. However the great challenge involved in the data interpretation is to achieve more reliable flood extent mapping including both the fully inundated areas and the 'wet' areas where trees and houses are partly covered by water. This is a typical combined pure pixel and mixed pixel problem.**

In this paper, an extended Support Vector Machines method for spectral unmixing developed recently has been applied to generate an integrated map showing both pure pixels (fully inundated areas) and mixed pixels (trees and houses partly covered by water). The outputs were compared with the conventional mean based linear spectral mixture model, and better performance was demonstrated with a subset of Landsat ETM+ data recorded at the Daly River Basin, NT, Australia, on 3rd March, 2008, after a flood event.

Keywords- Extended Support Vector Machine, Flood Mapping, Remote Sensing

I. INTRODUCTION

Australia, due to its climate, physiography, vegetation type and patterns of human settlement along rivers, coasts and across marginal agricultural land, is prone to a vast range of natural hazards and disasters [1]. Floods have been estimated to contribute 29% of the average annual natural damage in Australia. They cost around $314 million each year and are the most expensive natural disaster in Australia [2].

In recent years, remote sensing technology has opened an opportunity to cover every aspect of flood disaster management such as preparedness, prevention and relief. Generally a time instantaneous portrait of a flood stage over a wide area can be expected to be generated from remote sensing data. Active research has been conducted in recent years to map the extent of a flood by using optical or radar data due to their effectiveness and availability, as well as low cost [3]. Satellites like IRS 1C/1D with three sensors: PAN, LISS-3 and WiFS; NOAA (AVHRR) and Landsat -7 ETM+ provide data for various flood characteristics. Optical images are relatively easy to interpret, although it is challenging to delineate the land-water interface, overcome cloud cover and map flood boundary [4]. A number of automatic information extraction algorithms have been developed over the years including the use of water indices such as Normalized Difference Water index (NDWI) [5], the difference between Land Surface Water Index and Enhanced Vegetation Index (EVI) [6], PCA transformation [7], and supervised Maximum Likelihood classifiers [8,9]. The most complicated part in optical data interpretation is to separate the fully inundated from the 'wet' areas where trees and houses are partly covered by water. This is a typical combined pure and mixed pixel problem.

Generally it is assumed that every spot on the ground can be labeled as belonging to one and only one category. A classification algorithm produces a "likelihood" function and based on it to assign a class label to each pixel. This type of classification method is called hard classification. Level Slicing and Maximum Likelihood classifiers are examples of hard classification techniques [9, 10]. While such discrete categorization is convenient and simple to deal with, it is not a particularly accurate portrayal of real landscapes.

Since each pixel's spectrum is the result of the spatial average over the ground-projected spread function, it is inevitable that multiple spectral categories will be included in most of them, since there is often more than one ground cover type within a pixel (the size of spatial resolution). Spectral unmixing has been investigated for a long time which analyzes the proportions of primitive classes (endmembers) contained in each mixed pixel. This is called soft classification. The conventional spectral unmixing algorithms assume that the measured radiance is a linear combination of the mean radiance of the "pure" constituents in each of the imaging wavebands used [11]. Their weakness is that they don't model the spectral variations within a primitive class. This paper adopts a better technique called extended support vector machine (u_ESVM) [12] developed recently in order to obtain more reliable fractions of flood inundated areas. The outputs were compared with the conventional mean based linear spectral mixed model, and better performance was demonstrated with a subset of Landsat ETM+ data recorded at the Daly River Basin, NT, Australia, on 3rd March, 2008, after a flood event.

II. METHODOLOGY

Conventional spectral unmixing is a procedure by which the measured spectrum of a mixed pixel is decomposed into a collection of constituent spectra, or endmembers and a set of corresponding fraction or abundances are resolved to indicate the proportion of each endmember present in the pixel. An analytical model like Linear Mixing Model has often been applied for spectral unmixing. In this model a mixed pixel's reflectance at band n, Sn, is assumed as a weighted sum of all the endmembers [11].

$$s_n = \sum_{m=1}^{M} f_m a_{m,n} + e_n, \qquad n = 1,\ 2,\ \dots\ N \quad (1)$$

Where $a_{m,\,n}$ is the reflectance of endmember m at band n, f_m is the fraction of the endmember, M is the number of endmembers, and e_n is the residual error. However, in fact, the in-class spectral variation is often large and the fractions obtained from (1) can be negative or not sum to unity. To make the output meaningful, the fractions of the endmembers are constrained by [13]:

$$\sum_{m=1}^{M} f_m = 1 \;\; and \;\; 0 \le f_m \le 1 \qquad (2)$$

While it is a practical solution to impose the two constraints, the real problem of spectral variation within a class is not addressed. It is inappropriate to expect the pixels belonging to the same class to have the same spectrum.

Recently, the potential of support vector machine (SVM) in providing new understanding of mixed spectral data was investigated. The key essence of the SVM based approach to classification is that it seeks to fit an optimal hyperplane between classes and may require only a small training sample [14]. An extended version of SVM has been developed for spectral unmixing (u_ESVM) [12]. In this method, the complete set of training samples is used to model the pure pixels of the defined class. Fig. 1 illustrates this method with a simple case of 100% separability between classes of A and B in a two dimensional case. The support vectors now become the pixel vectors which are on the boundary between pure and mixed regions and are then named as 'just pure' pixels. The two regions above or below the lines formed by the 'just pure' pixels are pure pixels. The region between the lines is associated with the mixed pixels. If spectral mixture is assumed linear, the SVM decision boundary (in the middle of this region) becomes a 50% mixing line.

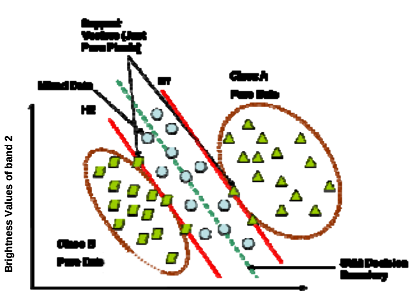

Figure 1. Spectral Unmixing with Extended SVM.

To perform spectral unmixing, the lines H1 and H2 as shown in Fig. 1 are determined first, and then the distances to the two lines are evaluated. The results represent the fractions of the two classes contained. For more than two class cases, the one-against-all approach can be adopted. The u_ESVM is conducted for each class against the rest of the classes separately to find out a pixel's relative mixture proportion, $\beta^r_{\mathbf{x}}(\omega_i)$. An extra step for this case is to normalize the mixture fraction by

$$\beta_{\mathbf{x}}(\omega_i) = \beta^r_{\mathbf{x}}(\omega_i) / \sum_{i=1}^{I} \beta^r_{\mathbf{x}}(\omega_i) \quad (3)$$

So that, $\sum_{i=1}^{I} \beta_{\mathbf{x}}(\omega_i) = 1$, where I is the total number of classes [12].

Since all the training data are used to form the boundary for pure and mixture regions, this model accommodates the spectral variation better, and is suitable for flood data interpretation, where most pixels from a given class do not have exactly the same spectrum. That is the reason that experiments were conducted by employing this technique.

III. Experiments and Results

The study area is located at the Daly River Basin, NT, Australia. Remotely sensed data used in this study was recorded by the Landsat-7 ETM+ on 3rd March, 2008, after a flood event. The spatial resolution is 30m x 30m. With this pixel size, a large portion of mixed pixels will exist as illustrated in Fig. 2 In this study all the bands of Landsat images were used.

Figure 2. An Example of Mixed Areas of Water and Vegetation.

Three basic classes were taken into consideration. Considering the flood situation, two classes have been defined for water bodies; those are Pure Flood Water and Turbid Flood Water. The third class consists of Non-water or Land. Three training sets were selected to train the supervised unmixing algorithm, u_ESVM. Three testing sets were selected to test if the unmixing model is reliable for the data other than training data (Fig. 3).Table. 1 gives the details of classes defined and the numbers of training and testing samples.

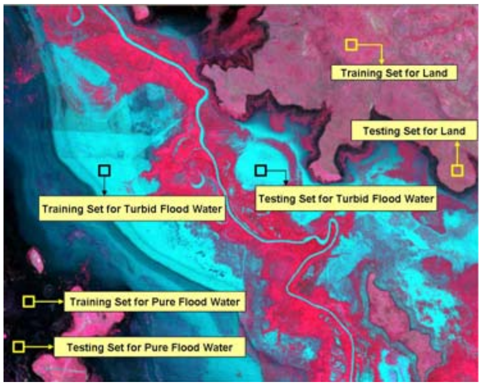

Figure 3. Training and Testing Sets

TABLE I. CLASSES DEFINED AND NUMBER OF TRAINING AND TESTING SAMPLES SELECTED

	Class	No. of Samples
Training Data	Pure Flood water	106
	Turbid Flood water	106
	Land	106
Testing Data	Pure Flood Water	106
	Turbid Flood Water	106
	Land	106

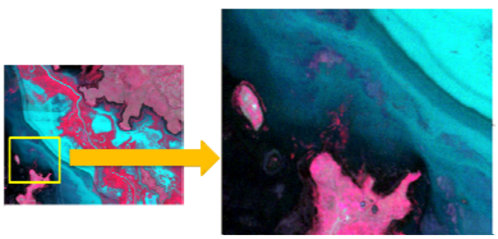

Figure 4. Subset Image

Since there is no ground truth information available for the mixed pixels, the performance is assessed using the pure pixels instead. We expect a binary unmixing result of 1 for the class the pixel belongs to, and 0 for other classes. Therefore for each class, the average unmixing accuracy for class is obtained as

$$acc(\omega_i)(\%) = \frac{\sum_{k=1}^{N_i} \beta_{\mathbf{x}_k}(\omega_i)^*}{N_i} \times 100\% \qquad (4)$$

Where N_i is the number of (pure) ground truth samples for class ω_i.

After running the u_ESVM on a small subset of image as shown in Fig. 4 using multiclass u_ESVM, each pixel is obtained 3 fractional values for 3 classes and the sum of those three fractions are equal to 1 for every pixel. Fig. 5 shows the unmixing results.

Unmixing using the mean based linear spectral mixture model given in (1) was performed as well for comparison using the popular remote sensing software ENVI, where the constraint of sum to unity was applied. This method is termed as u_CLSM. The unmixing results are given in Fig. 6. We can see the good feature of the resulting images obtained from u_ESVM is an integrated hard and soft classification where there is not only a large portion of mixed pixel but a reasonable amount of pure pixels. This is more realistic, comparing with other soft classification method where almost every pixel is recognized as mixed pixel.

Table 2 shows the unmixing accuracy on the training and testing data obtained from two methods. We can see that u_ESVM performs better in most of cases.

TABLE II. UNMIXING ACCURACY FOR THE TRAINING AND TESTING DATA

Data	Class	Accuracy (%)	
		u_CLSM	*u_ESVM*
Training Data	Pure Flood water	95.91	98.39
	Turbid Flood water	96.10	98.39
	Land	95.38	97.97
Testing Data	Pure Flood water	87.15	91.36
	Turbid Flood water	98.48	94.96
	Land	88.00	96.34
Overall Accuracy	Training Data	95.80	98.25
	Testing Data	91.21	94.22

IV. CONCLUSION

With the help of extended support vector machine a more realistic mixed pixel analysis is presented in this study. Both pure pixels and the mixed pixels are recognized and quantified.

Spectral unmixing provides more detailed information within a pixel. This can be further used for sub-pixel mapping, which will be the subject of further work.

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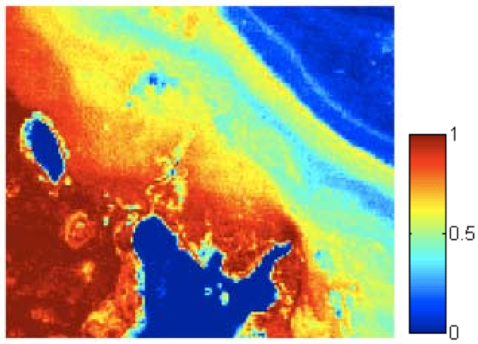
REFERENCES

[1] Middelmann, M. H., Natural Hazards in Australia Identifying Risk Analysis Requirements, Geoscience Australia, 2007.

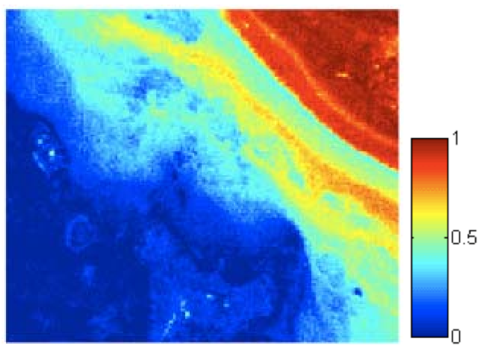
[2] Economic Costs of Natural Disasters in Australia, Bureau of Transport Economics, 2001.

[3] Y. Wang, “Mapping the Extent of a Flood: what we have learned and how we could do better”, Natural Hazards Review, 2002, vol.3, pp.68-73.

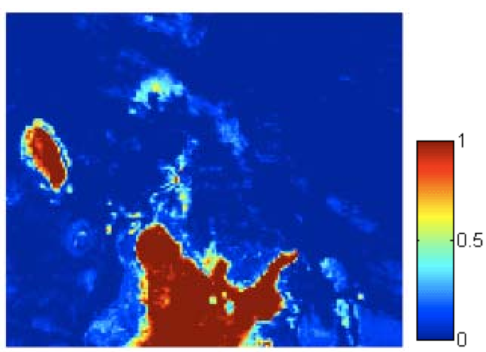
[4] Lillesand, T. M. and R. W. Kiefer, Remote Sensing and Image Interpretation, John Wiley and Sons, Inc, 2004.



(a)

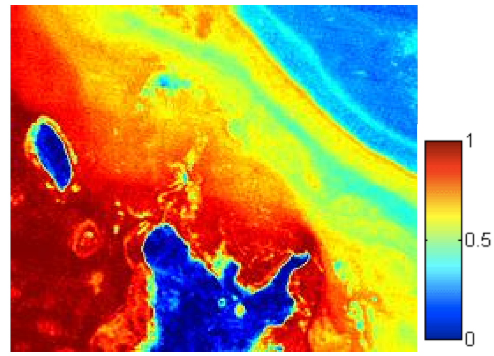


(b)

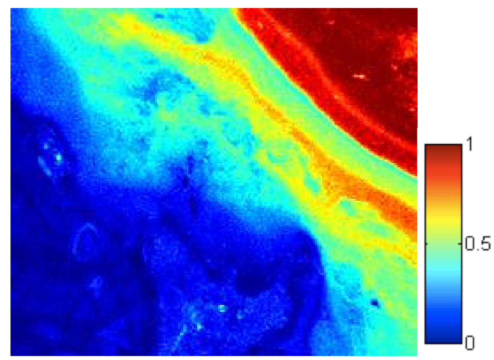


(c)

Figure 5. The Fraction Images obtained from Spectral Unmixing Analysis using Extended SVM (u_ESVM). (a) Fractions of Pure Water, (b) Fractions of Turbid Water and (c) Fractions of Land.



(a)



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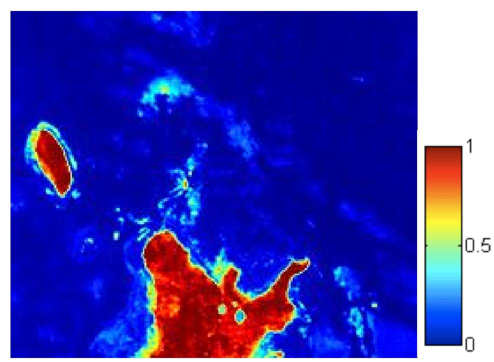

(c)

Figure 6. The Fraction Images obtained from Spectral Unmixing Analysis using Constrained Linear Spectral Mixture Model (u_CLSM). (a) Fractions of Pure Water, (b) Fractions of Turbid Water and (c) Fractions of Land.

[5] B. C. Gao, “NDWI: A normalized difference water index for Remote Sensing of Vegetation Liquid Water from Space”, Remote Sensing of Environment, 1996, vol.58, pp.257-266.

[6] T. Sakamoto, N. V. Nguyen, A. Kotera, H. Ohno, N. Ishitsuka, and M. Yokozawa, “Detecting Temporal Changes in the Extent of Annual Flooding within the Cambodia and the Vietnamese Mekong Delta from MODIS Time-series Imagery”, Remote Sensing of Environment, 2007, vol.109,pp.295 –313.

[7] P. F. Hudsona, and R. R. Colditz, “Flood Delineation in a Large and Complex Alluvial Valley, Lower Pa´nuco Basin, Mexico”, Journal of Hydrology, 2003, vol.280, pp. 229–245.

[8] J. Low, S. C. Liew, and L. K. Kwoh, “Automated Near-Real time Flood Detection and Mapping Using Terra MODIS”, Proceedings of the 25th Asian Conference & 11th Asian Space Conference on Remote Sensing, Chiang Mai, Thailand, November 22 - 26, 2004.

[9] P. K. Frazier, K. Page, J. Louis, S. Briggs, A. L. Robertson, “Relating Wetland Inundation to River Flow using Landsat TM Data”, International Journal of Remote Sensing, 2003, vol.24, pp. 3755-3770.

[10] Richards, J. A., and X. Jia, Remote Sensing Digital Image Analysis, Springer-Verlag,Germany, 2006.

[11] J. B. Adams, M. O. Smith, and P. E. Johnson, “Spectral Mixture Modeling: a new analysis of rock and soil types at the Viking Lander I site,” Journal of Geophysical Research, 1985, vol. 91, pp. 8098-8112.

[12] L. Wang, and X. Jia, “Integration of Soft and Hard Classification using Extended Support Vector Machines”, IEEE Geo-science and Remote Sensing Letters, 2009, vol.3.

[13] D. C. Heinz, and C. I Chang, “Fully Constrained Least Squares Linear Spectral Mixture Analysis Method for Material Quantification in Hyperspectral Imagery,” IEEE Transactions on Geoscience and Remote Sensing, 2001, vol. 39, pp. 529-545.

[14] G. M. Foody, and A. Mathur,"A Relative Evaluation of Multiclass Image Classification by Support Vector Machines", IEEE Transactions on Geoscience and Remote Sensing, 2004 vol.42, pp.1335-1343