Reducing Spectral Signature Confusion of Optical Sensor-based Land Cover Using SAR-Optical Image Fusion Techniques

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Abstract: Optical sensor-based land cover categories produce spectral signature confusion along with degraded classification accuracy. In the classification tasks, the goal of fusing data from different sensors is to reduce the classification error rate obtained by single source classification. This paper describes the result of land cover/land use classification derived from solely of Landsat TM (TM) and multisensor image fusion between JERS 1 SAR (JERS) and TM data. The best radar data manipulation is fused with TM through various techniques. Classification results are relatively good. The highest Kappa Coefficient is derived from classification using principal component analysis-high pass filtering (PCA+HPF) technique with the Overall Accuracy significantly high.

Keywords: spectral signature confusion, land cover/land use classification, image fusion, Overall Accuracy.

1. Background

Classification of land cover is one of the primary objectives in the analysis of remotely sensed data, and many applications of remote sensing require the classification of the land surface into discrete land cover types and the distribution of these land cover types [1]. The objective of image classification is to automatically categorize all pixels in an image into land cover classes or themes. However, spectral signature confusion of land cover classes derived from optical sensor frequently degrades classification accuracy [2].

Multisensor image fusion is an effective means of exploiting the complementary nature of different data types. The motivation behind data fusion is to generate an interpretation of the scene not available with data from a single sensor, or to reduce the uncertainty associated with the data from individual sensors [3]. For an image segmentation or classification task, the goal of fusing data from different sensors is to reduce the classification error rate obtained by single source classification [4]. A variety of surface characteristics uniquely detected by SAR can lead to an improved capability to map land cover.

This paper describes the result of digital image land cover/land use classification derived from multisensor image fusion between JERS and TM data. In this study, classification procedures used to extract information from remotely sensed images are based purely on spectral characteristics. The spectral confusion signature comparisons are also performed to the classification derived from TM and fused images. Image fusion techniques applied in this study are wavelet, intensity-hue-saturation (IHS), PCA and HPF. Image fusion is conducted at the pixel level [5]. This study gives particular attention to the contribution of SAR data to resolve spectral confusion resulting from optical-based classification.

2. Test Area, Images Acquisition and SAR Speckle Filtering

The test site chosen for this study is Bandung-Indonesia, which is located in 107o27’00’’ - 107o36’55’’ E and 06o49’00’’ - 07o01’00’’ S, covering an area of about 300 km^2. The JERS image employed for this study was acquired on 22 June 1994 and TM on 4 July 1994.

The input JERS image is preprocessed or smoothed to reduce noise. To reduce the effects of speckle on the classification of imagery, filtering techniques for speckle reduction are commonly applied to the input JERS data. Additional features such as, textural features that can help in classification, can also be included.

Filtering techniques for speckle reduction with different moving window sizes were examined and the results were compared to each other. The performance of each filter was tested quantitatively and visually. Quantitative analysis was carried out by evaluating

Table 1. Performance of various SAR speckle filtering techniques (in 3x3, 5x5, and 7x7 window sizes)

No	Speckle filters	ENL	Structures preservation (Good, Fair or Poor)
1	Frost	0.73, 0.71, 0.68	F, F, F
2	Gamma	1.12, 1.45, 1.74	F, G, F
3	Gaussian	0.91, 1.09, 1.19	P, F, F
4	Kuan	0.73, 0.71, 0.68	P, F, G
5	Laplacian	0.38, 0.53, 0.57	F, P, P
6	Lee	0.70, 0.67, 0.65	F, F, F
7	Mean	0.91, 1.13, 1.30	P, G, F
8	Median	0.70, 0.79, 0.86	P, F, F

equivalent number of looks (ENL) within homogeneous regions, and visual analysis was performed by comparing linear and edge structures in the images. A higher ENL means a lower noise value and therefore a greater reduction in speckle. A good preservation of the structure information indicates superior speckle filtering performance.

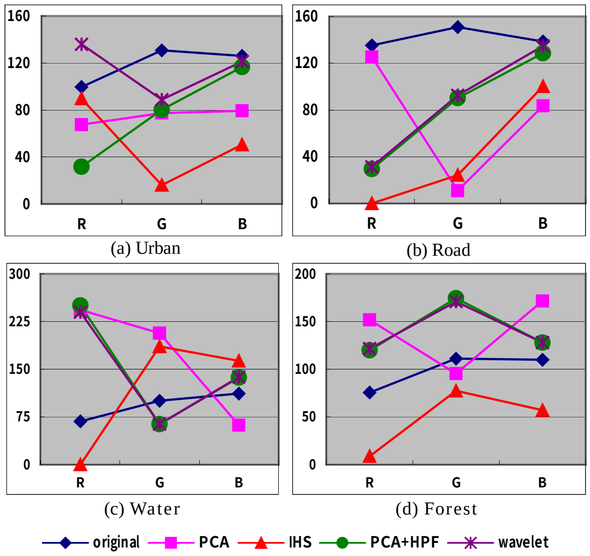

Fig. 1. Brightness values in each land cover/land use

3. Image Fusion Techniques

The wavelet transform applied in this study is a two dimensional Discrete Wavelet Transform (DWT). The original image is reduced in resolution by successive low-pass filter and subsampling [6]. After the wavelet transform the detail coefficients of the more highly resolved band (JERS data) and the approximation coefficients of the multispectral image (TM data) are used to create the synthetic wavelet image. Finally, the more highly resolved multispectral image is created using the inverse DWT.

In IHS technique, the Intensity component-the sum of the bands- is replaced with a stretched higher spatial resolution value (JERS data) and performing an inverse IHS transform. An inverse IHS transformation produces a new high resolution multispectral image [7].

The PCA in image fusion has two approaches: a) first PC of multi-channel image was replaced by different sensor image; b) all multi-image data channels were used as input to PCA procedure [8]. In HPF method, by adding this filter to the low resolution channel some of the high spatial information content of the high resolution image will become apparent in the fused product [9].

All sensor-specific corrections and enhancement of image data have to be applied prior to image fusion [5]. The JERS image is first registered to map coordinates and resampled by cubic convolution. The TM image is then registered by image-to-image procedure directly to their corresponding JERS and was resampled at the same resolution, also by cubic convolution, in order to avoid the blockiness due to the enlargement process. A minor coregistration error can lead to a slightly mismatched edge (edge-blurring problem).

The pre-processed TM and JERS data were merged using wavelet, IHS, PCA and the combined PCA and HPF techniques (PCA+HPF). In the first PCA technique, all channels of TM and JERS were used as input to PCA. In the PCA+HPF technique the high pass filtered JERS data was inserted into the three channels of the PCA product from TM image.

Grey level values of four land cover/land use classes were measured in the original and fused images for graphical comparison of the spectral effects of the fused techniques described above. Fig. 1 is the feature space plots showing the original image data alongside the four data fusion models for each scene. As can be seen, each of the image fusion techniques tends to modify the distribution of brightness values. The PCA technique has almost similar distribution of pixels as compared to the wavelet image. The spectral curves of the measured land covers/land uses, such as road, water and forest, are observed to be closer. However, in the forest area, IHS spectral curve has a similar fashion to that of the original image. Within the distribution though, PCA and wavelet techniques tend to eliminate brightness values in a systematic linear fashion.

4. Comparison of Classification Results

The digital classification methods using maximum-likelihood was initially applied to the TM data, then to the resulting fused data. A set of ground truth data points was selected for each class, half were used for training and half for testing. Training sites were selected using a combination of field surveys and land cover maps prepared by visual interpretation.

A confusion matrix (contingency table) was produced, and Overall Accuracy (OA) and Kappa Coefficients (K) were generated along with Producer's Accuracy (PA) and User's Accuracy (UA). Tab. 2 and 3 show the comparison of statistical significance among the output datasets.

The best results were achieved through the fusion of the best speckle filtered image (7 by 7 Gamma) with the

Table 2. Comparison of OA and Kappa coefficient

Image Classification	Accuracy (%)	Kappa
Original Image	70.28	0.68
Wavelet	81.69	0.76
IHS	54.83	0.51
PCA	83.69	0.78
PCA+HPF	86.80	0.86

Table 3. Comparison of PA and UA

Image classification	Accu-racy	Land cover/land use types				
		1	2	3	4	5
Original Image	PA	94.04	58.28	47.71	68.25	48.32
	UA	79.20	58.46	79.24	51.78	91.27
Wavelet	PA	85.44	79.82	61.63	98.36	84.36
	UA	89.29	86.11	68.52	94.48	70.30
IHS	PA	82.67	54.33	71.94	25.22	61.04
	UA	26.94	92.30	46.59	44.06	92.98
PCA	PA	85.51	81.99	93.82	99.18	53.98
	UA	83.62	75.22	89.65	96.76	84.32
PCA+HPF	PA	92.76	81.52	92.31	99.27	67.64
	UA	95.94	87.92	77.39	96.41	76.31

1=Forest, 2=Rural area, 3=Urban, 4=Water body, 5=Paddy field

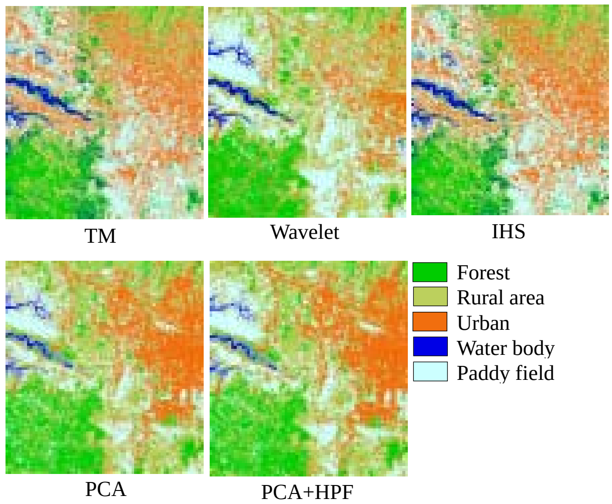

Fig. 2. Classification results of TM and the fused images

multispectral TM data using PCA+HPF technique. The Kappa value for this technique is very good (0.86) and the OA is significantly high (86.80 percent). The comparison for those techniques applied can be seen in Tab. 2. Except for IHS technique, classification results derived from multisensor image fusion are very good. In IHS technique the improved results are only for certain classes i.e., paddy field and urban land use types (Tab. 3). The results also suggest that JERS's sensitivity to surface roughness and moisture differences were contributing factors to improve the classification results by reducing spectral signature confusion of TM's classification. In TM's results, the water bodies, urban and paddy field were less resolved, so it reduces classification accuracy significantly. The classification results for original TM and fused images with various techniques are presented in Fig. 2.

6. Conclusions

The use of combination of radar and optical data would increase the accuracy of classification, because the data contains different information for target being sensed. Except in IHS technique, it was demonstrated that multisources classification techniques using image fusion between JERS and TM data yielded improved results compared to the classification result derived solely from TM data. In IHS technique, the results were only improved for a certain class. The JERS's sensitivity to surface roughness and moisture differences were contributing factors to improve the classification results by reducing spectral signature confusion of TM's classification. In this study, the Gamma filter at 7 by 7 window was determined to be most appropriate for despeckling the input JERS data. Future applications of this study will include a comparison of despeckeling noise performances using radiometric loss parameter and application of other classifiers.

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