Optimizing Classification Accuracy of Remotely Sensed Imagery with DT-CWT Fused Images

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Abstract. Image fusion is a basic tool for combining low spatial resolution multi-spectral and high spatial resolution panchromatic images using advanced image processing techniques. Study on efficient image fusion method for specific application is one of the most important objectives in current remote sensing community. On the other hand, it is well known that the image classification techniques combine complex processes that may be affected by factors like the resolution of remote sensed images. This study focuses on the influence of image fusion on spectral classification algorithms and their accuracy. Results are presented on SPOT images. The best results were achieved by Dual Tree Complex Wavelet Transform (DT-CWT)).

Keywords: Classification accuracy, Image fusion, Dual Tree Complex Wavelet Transform, DT-CWT.

1 Introduction

Remote sensing is a fundamental tool providing a relatively lower cost for the detection, classification and monitoring of landslide phenomena. Classification aims to convert the remotely sensed image into a thematic map that depicts the spatial distribution of the various land-cover classes found within the region. These maps have been used to analyze the impacts of land use change on the environment, improve land use planning and natural resource management, and better understand ecological processes on Earth. Of the many classification approaches available, most researchers use either supervised or unsupervised classification. Supervised classification consists of two stages: training and classification. In the training stage, the analyst identifies representative training areas and develops a numerical description of the spectral attributes of each land cover type of interest in the scene. In the classification stage, each pixel in the image data set is categorized into the land cover class it most closely resembles [1]. Unsupervised classification techniques do not utilize training data as the basis for classification. Usually supervised classifiers are preferred to unsupervised clustering algorithms, which are intrinsically less suitable to obtain accurate classification maps.

Classification of remote sensing images is a complex task whose accuracy strongly depends on the available prior information. In this sense, given the general high complexity of the problem, we need to dispose of high quality images. Image fusion techniques are useful to integrate the geometric detail of high spatial resolution panchromatic (PAN) image with the colour information of high spectral resolution multispectral (MS) image to produce a MS image with high spatial quality. High spatial resolution MS image data are indispensable for inventorying and monitoring of land surface phenomena [2].

A recent study shows the influence of image fusion on spectral classification for Landsat images, with acceptable results [3]. This paper analyzes the accuracy results of image supervised classification, which can be improved by using fused SPOT images obtained through multi-resolution analysis (MRA) by Dual Tree Complex Wavelet Transform (DT-CWT), compared with classical fusion algorithms.

2 Background

2.1 Fusion Methods

The advantage of a fusion process is that a single image can be achieved containing both the high spatial resolution and spectral information, hence, the result of image fusion is a new image which is more suitable for human and machine perception or further image-processing tasks such a classification, segmentation, feature extraction or object recognition. There are a variety of types of fusion, these range from a simple average of the pixels in registered images to a more complex schemes using multiresolution analysis (MRA) (pyramids, wavelets, etc), this variety of schemes have been developed over the last 25 years, with classical approaches such as IHS (Hue-Intensity-Saturation), PCA (Principal Component analysis) or HPF (High pass filter).

One step beyond, are the multi-resolution analysis (MRA), which provides effective tools to facilitate the implementation of data fusion and have shown a better performance when injecting the high frequency information extracted from de PAN into resampled versions of MS [4], by example A Trouws Wavelet transform ¹, Curvelet Transform ², Hermite transform ³. Here, it is necessary to consider that when injecting high-pass details, spatial distortions may occur, resulting in translations or blurring of the contours and textures, this occurs mainly when the MRA is not shift invariant [4].

There is a MRA algorithm, that is particularly suitable for images and other multi-dimensional signals processing, which is approximate shift invariance and computational efficiency with good well-balanced frequency responses, this will be described below.

¹ Zhu et al: Fusion of High-Resolution Remote Sensing Images Based on a trous Wavelet Algorithm, 2004.

² Nencini et al: Remote sensing image fusion using the curvelet transform, 2007.

³ Escalante et al, A.: The Hermite Transform An Efficient Tool for Noise Reduction and Image Fusion in Remote-Sensing, 2006).

2.2 Dual Tree Complex Wavelet Transform

An effective approach for conducting an analytical wavelet transform, originally introduced by Kingsbury in 1998, is called Dual Tree Complex Wavelet Transform, avoid unwanted frequency component and is also expansive, but only by a factor 2 (1-D signals), independent of the number of stages. The properties that characterize the DT-CWT are highlighted in several papers [5]. The principal properties are: good shift invariance, good directional selectivity in m-D, perfect reconstruction with short support filters, limited redundancy (2:1 in 1-D, 4:1 in 2-D, etc) and low computation, much less than the undecimated (à trous) DWT.

The Framework of the Dual-Tree. The DT-CWT uses two real DWTs, the first DWT delivers real part of transform while the second DWT delivers the imaginary part. FBS for the analysis and synthesis used to implement the dual-tree CWT and its inverse are shown in Figure 1.

Fig. 1. Filter Bank (FB) for DT CWT (a) Analysis (b) Synthesis

Here, $h_0(n)$, $h_1(n)$ are the pair of low pass filter / high pass to the superior FB (tree a), $g_0(n)$, $g_1(n)$ the pair of low pass filter / high pass for inferior FB (tree b). $\psi_h(t)$ y $\psi_g(t)$ are the two real wavelets associated with each of the two transform (tree a and b, respectively), below there are the features for the DT-CWT's filter banks.

- The two real wavelet transforms use two different sets of filters, each of whom meets the conditions for PR.
- In addition to satisfying the PR conditions, the filters are designed so that the complex wavelet $\psi := \psi_h(t) + j\psi_g(t)$ is approximately analytic.
- According to the above, are designed so that $\psi_g(t)$ is approximately the Hilbert transform of $\psi_h(t)$ (denoted by $H\{\psi_h(t)\}$).

- To satisfy this condition, one of the filters must have a displacement approximately half-sample with respect to the other [5]. Recent studies show alternatives to this classical approach^{4,5,6}.
- The filters themselves are real.
- The transform is twice expansive (not critically sampled).

3 Methodology

3.1 Scene Study

A multispectral (MS) and panchromatic (PAN) SPOT images were used in this study. The images have a spatial resolution of 10 m and 2.5 m and covered an area of the order of 26 km^2 . The scene consists of three great environmental blocks: to the left there are extensions of natural mediterranean forest partially degraded, in the central axis and crossing all the scene it is characterized by the city-planning, industrial advance and road infrastructures that degrade zones of agrarian development in other times and the right part are the vestiges of agricultural zones as a result of the Jarama river presence, one important of the community of Madrid (Spain). The left corner is placed at 450775 E and 4494685 N (UTM geographic coordinates, h30).

Eleven thematic classes have been supervised in situ: the water class corresponding to a reservoir and in a golf course; five vegetation types like the natural of degraded Mediterranean forest (oak forest), two zones of irrigated land crop, green of golf course and riverside vegetation; mixed area with vegetation and ground; clearly built-up ground with highway and three types of ground as soil in fallow land and without specific use. Thus, the names assigned for training areas have been: water, natural soil, crop1, crop2, green-golf, riverside vegetation, mixed soil, urban soil, soil1, soil2 and soil3.

3.2 Fusion Process and Quality Determination

From the increasing variety of image fusion methods, a selection of three fusion techniques was chosen, Principal Components Analysis (PCA) and two based on multi-resolution analysis: A Trous Wavelet Transform (AWT3) (3 levels) and Dual Tree complex Wavelet Transform (3 levels). For first two, we used the IJFusion framework⁷; for the last one, we propose a method using the toolbox for DT-CWT, provided by the Dr. Nick Kingsbury⁸. This method will be described below.

⁴ Tayet al.: Orthonormal Hilbert-Pair of Wavelets With (Almost) Maximum Vanishing Moments, 2006.

⁵ Bogdan et al.: Optimization of Symmetric Self-Hilbertian Filters for the Dual-Tree Complex Wavelet Transform, 2008.

⁶ Yu et al.: Sampled-Data Design of FIR Dual Filter Banks for Dual-Tree Complex Wavelet Transforms via LMI Optimization, 2008.

⁷ <http://www.ijfusion.es/>

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Fig. 2. Image Fusion with DT-CWT

Image Fusion with DT-CWT. The fusion process involves the following steps, see Figure 2.

1. The low-resolution MS image is resample to the size of the panchromatic image, after this process, the 2 images are the same size.
2. Implement the dual tree wavelet transform to MS bands and PAN image, a certain number of levels, for this particular case, we use 3 levels of decomposition.
3. Defines the coefficients of the DT-CWT decomposition for a new high-resolution MS image (HRMS). For these new coefficients is preserved approximation of the MS decomposition.
4. To calculate the details of the new HRMS are considered both the wavelet coefficients of the PAN as the MS, i.e., injecting the details of the PAN according to a weight that depends on the ratio of standard deviations for a neighborhood around the coefficient in question.
5. This procedure is carried out recursively from the lowest to the highest level.
6. Finally apply the inverse DT-CWT to new (HRMS) coefficients.
7. New bands come together to compose the merged image, this image not only contains the original spectral information but also the structure of information in the panchromatic image, i.e., improving both the spatial and spectral information of original images.

Image Fusion Assessment. To know the quality of the merged image, the new fused image is usually compared against a reference image (true), to create it, and having the sets of original images A_h and B_{KL} , where A denotes the PAN image, B the MS image, h high resolution, l low resolution and K each band of the MS; the image A_h is degraded to the low resolution l , giving A_l . B_{KL} images

Table 1. Metrics used for fusion assessment

Correlation Coefficient (CC) [6]	$CC(X, Y, k) = \frac{\sum_m \sum_n [(X_{mn}(k) - X'_{mn})(Y_{mn}(k) - Y'_{mn})]}{\sqrt{\sum_{m,n} (X_{mn}(k) - X'_{mn})^2 \sum_{m,n} (Y_{mn}(k) - Y'_{mn})^2}} \quad (1)$
	<i>K</i> : k-band, <i>X</i> : Original image, <i>Y</i> : Merged image, <i>MxN</i> : Image dimensions
ERGAS [7]	$ERGAS = 100 \frac{d_h}{d_l} \sqrt{\frac{1}{L} \sum_{l=1}^L \left(\frac{RMSE(l)}{\mu(l)} \right)^2} \quad (2)$
	<i>d_h</i> : PAN pixel size (m), <i>d_l</i> : MS pixel size (m) <i>L</i> : Number of spectral bands, <i>μ(l)</i> : Mean of each spectral band, <i>RMSE(l)</i> : <i>Root Mean Squared Error</i>
Spatial CC (SCC)	$CC(X_{hf}, Y_{hf}, k) \quad (3)$
	<i>X_{hf}</i> , <i>Y_{hf}</i> : High frequency image, obtained by means a Laplacian filter

are degraded to the resolution $l(l/h)$, giving B'_{kl} . The fusion process is applied to images A_l and B'_{KL} , the quality can be assessed using as a reference image the original MS image, i.e. B_{kl} . The metrics used are listed in the Table 1.

3.3 Classification Process

We employed a consistent classification scheme applied to each fusion result using two supervised parametric and non-parametric classifiers. Within the parametric classification approaches, the maximum likelihood classification (MLC) algorithm [8] is one of the most applied methods. In contrast to the maximum likelihood classifier, support vector machines (SVM) [9] can be used as nonparametric or discriminative, binary classifiers. In this study, the two classifiers above mentioned have been used.

Since supervised methods have been considered, the first step is the definition of a set of training areas in the images to be classified. This process is critical because these areas would be used like an estimator of the land cover classes. The selection of training areas has been carried out through a two-dimensional scatter diagram (scattergram) methodology [10].

Then for supervised classification, the training areas were selected according to eleven thematic classes derived by scattergram methodology, visual image inspection and field work. The total number of training areas pixels were 130 per class approximately. Additionally, a 10% of test samples for accuracy assessment were collected and treated separately. For fused images, the training and test areas were selected in the same geographical location. Each classification was performed and assessed with identical training and test samples.

When the remote sensing images were classified, the accuracy of each classification was assessed using statistical method [11]. Error matrices were constructed, then overall accuracy (OA) and the kappa index (K) were calculated

to assess the whole accuracy of the classified map, and the producer accuracy and user accuracy were used to interpret the success of each class.

4 Results

The Table 2 shows the results in each band (b1:green, b2:red, b3:NIR y b4:SWIR) for the quality indexes used in this work. The proposed method (DT-CWT3) shows high spectral quality with high spatial quality; better results in spatial quality were achieved with the simple injection of PAN details (DT-CWT3P), but with a slightly lower spectral quality. In general terms, the DT-CWT is a good approach for image fusion, reaching better results than traditional schemes.

Table 2. Results for image fusion

	ERGAS	CC				SCC			
	b1-b4	b1	b2	b3	b4	b1	b2	b3	b4
PCA	7.4184	0.9701	0.9739	0.9196	0.938	0.9944	0.9982	0.9575	0.9924
AWT3	1.7987	0.9737	0.9863	0.7893	0.8776	0.9995	0.9994	0.9993	0.9994
DT-CWT3P	1.7581	0.9735	0.9884	0.8104	0.883	0.9994	0.9993	0.9982	0.9989
DT-CWT3	1.3945	0.9827	0.987	0.8653	0.9216	0.9946	0.994	0.9928	0.9941

The results of the accuracy classification are showed in the Table 3. In all cases, the overall accuracy (OA) and the kappa (K) index are good. The best results are achieved in the classifications of fused images obtained by DT-CWT. In general, user's accuracy of natural soil class is lower (60.87-82.35%) than the others classes. There is a considerable confusion with riverside vegetation class in the case of AWT3 fusion. This mis-assignment was caused by the mixed and variable spectral response of the natural soil class, which comprises a wide variety of surface cover types.

Table 3. Accuracy Parameters of Image Classification

	MULTI		PCA-Fus		AWT3-Fus		DT-CWT3-Fus	
	MLC	SVM	MLC	SVM	MLC	SVM	MLC	SVM
OA (%)	95.6	97.2	94.2	96.7	95.6	95.4	98.5	97.5
K	0.951	0.969	0.936	0.964	0.951	0.949	0.984	0.973

5 Conclusions

In this study focused on the influence of image fusion approaches on classification accuracy, three fusion approaches were applied to a SPOT image. The fusion results were employed for supervised classification with two methods (MLC and

SVM). High values of classification accuracies of fused and no fused images are obtained. From evaluations with fused images, the following ranking was derived (from best to poorest): Dual Tree Complex Wavelet Transform (DT-CWT), A Trous Wavelet Transform (AWT) and Principal Component Analysis (PCA).

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