A PRECISE TEXTURE-COLOR BASED FOREST DETECTION IN URBAN ENVIRONMENT

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KEY WORDS: Wavelet, Texture-color, IKONOS, post-classification

ABSTRACT:

Woodland detection in an urban environment was conducted using Ikonos multispectral images over the city of Sherbrooke (Quebec, Canada). The detection process is composed of two parts. The first is a combination-based classification that uses radiometric and color-texture information. The color-texture feature is derived by integrative scheme using the wavelet transform. The second part is an object-based post-classification process. The overall classification accuracy of the first step was in the order 82%, however the post-classification brings a significant improvement of 12% to the final classification.

1. INTRODUCTION

The insufficiency of the classical classification scheme, based on the radiometric information, when dealing with high resolution satellite images (TM, SPOT, ERS...) has been reported early in the literature (Haralick, 1973; Emran, 1996; Kurosu,1999; Lu, 2005; Manian, 2oo5). With the commercialization of the very high resolution satellite images (Ikonos, QuickBird) it is henceforth possible to identify finer ground details. Classification process applied to these images has followed this tendency while trying to identify more details, often while adding other information such as the texture or the context. This situation is accentuated when dealing with a complex environment such as the urban one (Shackelford, 2003; Herold, 2003; Martino, 2003; Puissant, 2003). Even though, the task is a challenge, the results do not necessary follow. Indeed, the noise caused by strong details level present in these images affects severely the cartographic value of the produced maps, making them poor for a GIS input.
The objective of this work is to propose a methodology that takes advantage of the improvement of the spatial resolution, and which minimizes the drawback of the high ground fragmentation.
Texture information with color, are two visual keys when interpreting information on remote sensing images. Indeed, the response of the human visual system depends on a multitude of image features, such as the wavelength (color) of the visual stimulus and its spatial frequency content (Wuerger, 2003). Measuring texture in combination with color information, rather than color or texture alone, yields to color-texture features. This combination has gained attention in recent years. In (Palm, 2004), color texture combination approach was divided to parallel, sequential and integrative.

The thematic of our application is with the land use mapping in a diversified environment (urban and rural). The proposed approach is divided in two steps. The first is a radiometric and color-texture based classification of an Ikonos multispectral image. Color-texture features are extracted with the integrative approach. The second step is a post-classification object-oriented hierarchical reclassification

2. AREA OF STUDY

The present study is conducted using a multispectral Ikonos image (spatial resolution of 4m).The image covers the city of Sherbrooke (Quebec, Canada). It lies between the latitudes 45°27'31.74"N and 45°20' 10.31"N and between the longitudes 71°58' 0.68" W and 71°48' 13.78"W. it covers a total surface of 100 km2.
The image consists of an urban and rural environment. The urban landscape is composed of: road, commercial and residential buildings, parks, grass, agriculture, forest, bare soil and water. Fig. 1 gives an overview of the study area.

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3. COLOR-TEXTURE FEATURE

3.1 Wavelet transform

In contrast to texture which is looked at as a pure spatial phenomena, the color-texture is a spatio-chromatic pattern, which may be defined as 'the distribution of the color over a surface' (Paschos, 2001). In this paper the color-texture feature is extracted using wavelet transform. Wavelets are functions whose general form is given by:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right), \quad (a,b) \in \mathrm{R}^2, \ a \neq 0 \qquad (1)$$

Where *a is* the scale factor and *b* is the translation parameter. The main advantage of using wavelet transform in feature extraction, is the scale-space analysis and the orientation capabilities.

3.2 Texture-color extraction

The color-texture information is extracted using the wavelet energy correlation (Van de Wouwer, 1997). The basic idea of this approach is the use of color space transformation to insure a weighting of the texture and color information. Eq. (2) illustrates the general form of the color-texture feature used in this study. An detailed description of the color-texture concept may be found in (Van de Wouwer, 1997, Safia, 2006).

$$E_{ni}^{X'_j} = C_{ni}^{X'_j X'_j} = \sum_{r,s=1}^{3} m_{jr} m_{js} C_{ni}^{X_r X_s} \qquad (2)$$

where C_{ni} : the covariance matrix coefficients
M(m_{jr}) : the color space transformation matrix
X: the original Neighborhood
X´ = M * X is the transformed neighborhood
i gives the four wavelet transformed images
n gives the wavelet decomposition level

The second order spline bi-orthogonal wavelet is used. This wavelet is often used in texture analysis, for its good localization in the space-frequency domain. This wavelet is very sensitive to the local variance, singularity and scene correlation (Chang, 1993; Unser, 1995). Thus, it is considered appropriate for image texture analysis.

3.3 Color-texture extraction parameters

The correlation between the Ikonos bands, which is reflected in the correlation coefficient, is very high because the sections of the spectrum that correspond to each band are very close. As the color-texture extraction algorithm needs three input channels, we have to select the optimum combination. We have used the method proposed by Chavez et al (Chavez, 1982). Puissant (2005) based on the calculation of the Optimum Index Factor (OIF) which maximizes the channels variance and minimizes the correlation between channels. The selected bands are the bleu, red and near infrared.

A one level wavelet transform was applied to the images. For each of the four images (approximation image, horizontal, vertical and diagonal details images) of the three selected bands, the color-texture feature was calculated locally using a moving window of 5x5 pixels. Two criteria were retained in the empirical selection of the windows size. The first is a visual contrast analysis of the feature images. The second is the fine details preservation in the feature images.

A minimum distance algorithm using Mahalanobis was applied for image classification. The supervised classification process uses the three color transformed original bands in addition to the color-texture bands.
The thematic information contained in the image is grouped in six classes: 1) residential urban, 2) commercial urban, 3) forest-woodland, 4) agriculture-grass, 5) water, 6) bare soil.

4. RESULTS

Training and verification sites were chosen for a supervised classification need. The classification accuracy for each class is given by the confusion matrix Tab 1. The overall classification rate is 82.42%. Fig. 2 shows part of the classified image.

	Ground truth (pixels)					
	1	2	3	4	5	6
1	480	228	14	0	0	0
2	63	383	0	0	0	14
3	167	40	1089	11	0	3
4	3	4	108	770	0	1
5	2	44	4	0	388	1
6	30	133	0	0	0	969
%	64.4	46.0	89.6	98.6	100	98.0

Table 1. Confusion matrix, 1) residential urban, 2) commercial urban, 3) forest-woodland, 4) agriculture-grass, 5) water, 6) bare soil.

As can be seen on the confusion matrix (table 1), we have obtained a good detection of the themes: forest-woodland, agriculture-grass, bare soil and water where the rate of right classification exceeds 89%. For the other two themes (urban residential, urban commercial) the precision obtained is less than 46%. This low rate is due to the mixed nature of the two themes. This confusion will be taken into consideration further in this paper.

Figure 3 gives the forest-woodland mask obtained by the color-texture and radiometric based classification. As we have mentioned in the introduction and even if the result was precise enough, the land use map remains very fragmented. We will apply later a post classification process so that to improve the precision and the cartographic value of the produced woodland mask.

Figure 1. Ikonos multispectral image

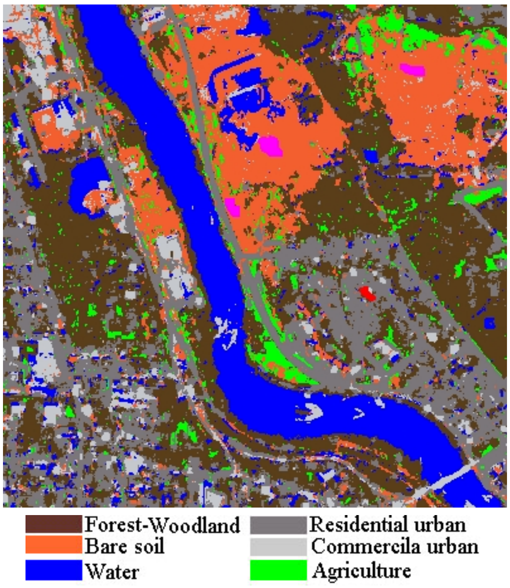

Figure 2. Color-texture classification

Figure 3. Forest-woodland mask (with no post-classification)

5. POST-CLASSIFICATION PROCESS

It is often reported in the literature that the insufficiency of the per-pixel classifications in terms of homogeneity is due to the random noise called 'salt and pepper'. Recently, a new approach called the object oriented analysis has been developed to overcome this problem. It is based on the image segmentation followed by a classification process of the objects (segments) generated through the segmentation phase (Baatz, 2000). This approach has had many usages (Niemeyer, 2002; Benz, 2004; Laliberte, 2004). The error risk involves not only a single pixel but a set of pixels (object).

It is important to recall that if the radiometric value of a pixel is augmented with other measures, such as the texture for example, and if we apply in the output the appropriate post classification process, the per pixel classification will be, by far, the most safer way to insure the best classification rate compared to the per object classification. Because in the per pixel classification, the majority of the pixels are well classified and the errors are often easily detectable.

In this paper, the post-classification process is applied on the initial classification which uses the color-texture feature and is composed of:

5.1 First step

The importance of a pixel or group of pixels in a classified image depends on the nature and the context of the class and finally the application aim. A group of pixels classified as Greenland for example can undertake the following changes:

- Re-affected towards the main class in the case where the number of pixels (surface) is insignificant.
- Context based reclassification: for example, trees in an urban environment may be classified as forest class. This is correct from the spectral response point of view. A generalization process through the context information would reclassify this area as woodland, which is a more precise classification from a human interpretation perspective.
- Maintain the class as Greenland if it is located in a forest zone and the objective of the study is for example, forest degradation monitoring.

The aim of this first phase is to establish for each class the different rules to be applied in the post-classification process.

5.2 Second step

The second step is with the classified image segmentation and the application of different rules as mentioned in the first step. According to fig. 4, the set of the post-classification process operations are as follow:

(1) Initial classification using color-texture features
(2)Per-class analysis
(3) Per-class contextual post-classification
(4) Intermediate classification
(5) Urban/non-urban mask building
(6) Class spliting
(7) Hierarchical Classification

Figure 4 shows the flowchart of the post-classification process.

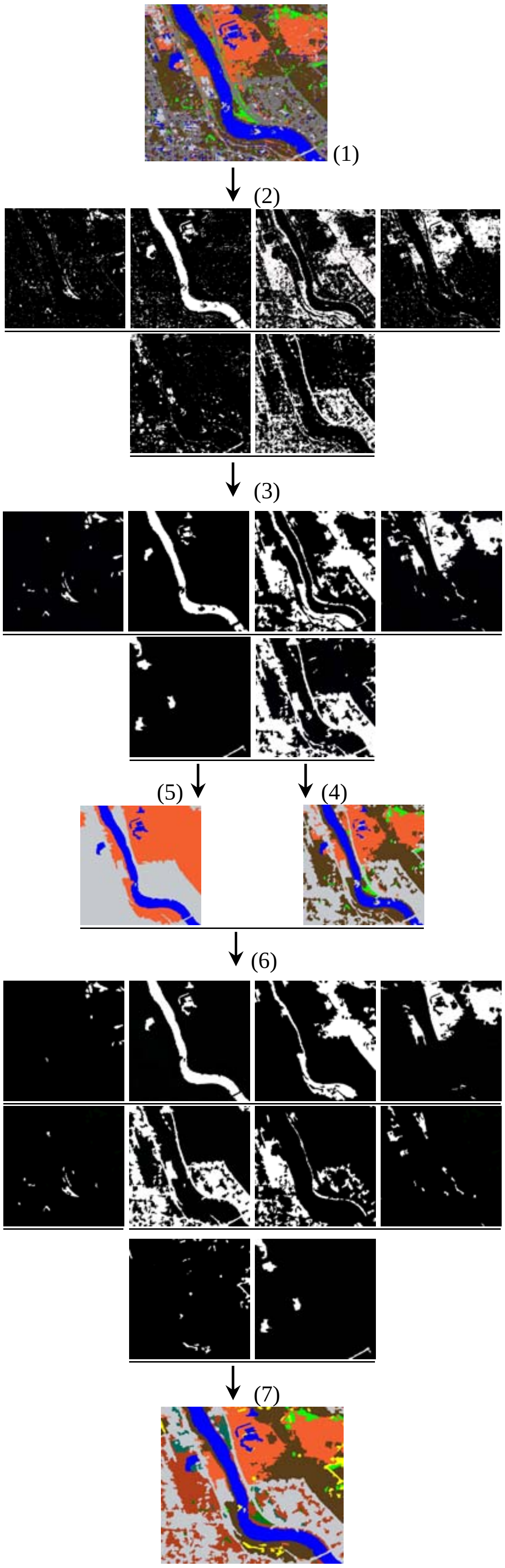

Figure 4. Flowchart of the general methodology

6. RESULTS

The confusion matrix calculated for the output image of the post-classification process is given in table 2. The new land use map legend (improved the legend from 6 to 10 classes) is as follow: 1-woodland, 2-grass, 3-urban bare soil, 4-commercial urban, 5-water, 6-forest, 7-agriculure, 8-rural bare soil, 9-rural urban, 10- residential urban. The results show that the post-classification process brings a significant improvement of 12% to the overall classification accuracy.
Fig. 5 gives a part of a final classification image.

Ground truth

	1	2	3	4	5	6	7	8	9	10
1	98.9	2.6	2.7	0	0.3	0	0	0	0	2.2
2	0	97.4	0	0	0	0	0	0	0	0
3	0	0	87.5	12.0	0	0	0	0	0	2.5
4	0	0	8.8	83.9	0	0	0	0	0	0
5	0	0	0	0	99.7	0	0	0	0	0
6	0	0	0	0	0	94.8	0	0	2.9	0
7	0	0	0	0	0	5.2	100	0	0	0
8	0	0	0	0	0	0	0	99.2	2.6	0
9	0	0	0	0	0	0	0	0.8	94.5	0
10	1.1	0	1	4.1	0	0	0	0	0	95.3

Class classification accuracy (%)

Table 2. Post-classification process confusion matrix

The use of the post-classification process has allowed the refinement of the land use map nomenclature (fig. 5). Indeed, we were able to distinguish between forest and woodland, agriculture and grass. Except for the commercial areas and the bare soil classes, all other themes have been classified with accuracy higher than 94.5%. This confusion is due to a particular type of roofs which have strong similarities with the bare soil. Fig.6 gives the forest-woodland mask obtained after the post-classification process. The comparison with fig. 3 gives an idea of the performance of the proposed post-classification approach. The separation between these two classes is made by applying image mask (fig. 8). The result is given in fig. 7. The urban/non-urban mask (fig. 8) gives a realistic approach to the urban extension assessment.

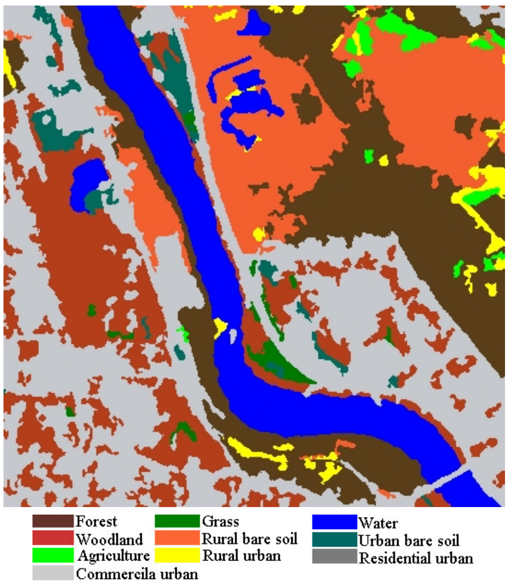

Figure 5. Final classification

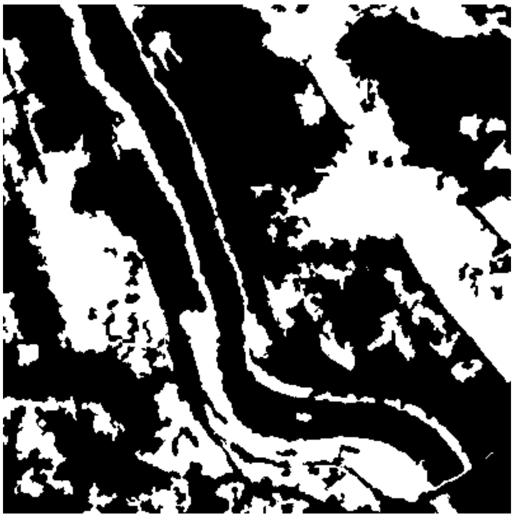
Figure6. Forest-woodland mask (with post-classification approach)


Figure7. Woodland mask

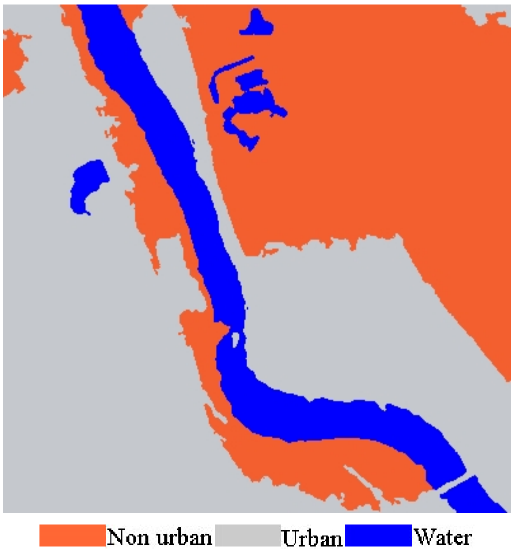

Figure8. Urban/non u urban mask

Fig 9 and 10 give forest and woodland delimitation in other site of the image.

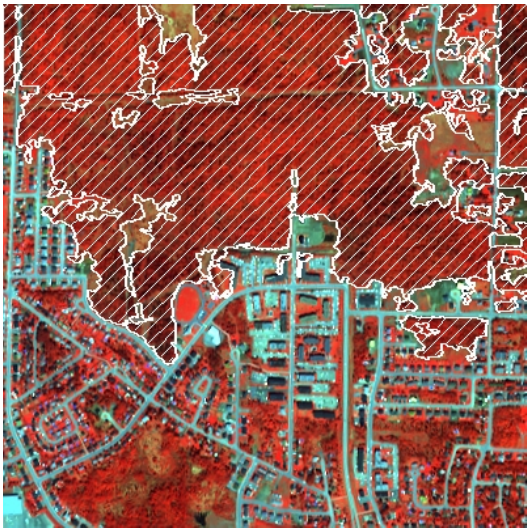
Figure9. Forest class


Figure10. Woodland class

7. CONCLUSION

This study presents two main points. The first is the fusion of texture and color information in high resolution satellite imagery for a classification process in a mixed area. The second is the use of an object based contextual post-classification process to improve the classification output quality (for GIS use).

The results show that the use of color-texture feature derived with an integrative strategy using the wavelet transform insures good classification accuracy in a relatively complex mixed area. The overall classification accuracy was about of 82.42%.
The use of the proposed post-classification strategy brings a significant improvement of 12% to the overall classification rate rendering therefore the final land use map highly attractive to GIS studies.

8. REFRENCE

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