CHANGES AT MULTIPLE SPATIAL SCALES

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ABSTRACT

Change detection on rasterized data is extremely dependent on accurate radiometric and geometric rectification. The development of processing tools able to minimise these requirements has been recognised since the late eighties. In the present paper we present a methodology for detecting changes on multidate satellite images with different radiometric and geometric characteristics via Multiresolution Wavelet Analysis. An area in south-eastern Brazil was chosen as case study. In the last 20 years the site was characterised by an increase of mining activities and deforestation. Landsat TM and MSS images from July 1981, November 1985 and August 1998 were used. The idea is to decompose a set of images into averages (overall pattern) and details images at different resolutions. Image differences due to the effects of spatial misregistration, atmospheric condition and sensor characteristics are depicted across scales. No radiometric rectification was applied to the input images and the spatial misregistration ranged from one to three pixels. To detect deforestation and new mining areas we used details at the third and fourth scales. Deforested areas as well as new mining sites were successfully pinpointed without previous radiometric rectification or threshold definition while differences not related to land cover changes were bypassed. Misregistration effects and small area changes are depicted as fine details. Phenological characteristics, atmospheric effects and differences in sensor calibration are represented at coarser scale levels. Hence, using information from intermediate scale levels one can minimise the problems mentioned above.

1 INTRODUCTION

Multitemporal and multisensor analyses of satellite images are becoming important research fields in geo-information sciences. This is mainly due to large quantities of remotely sensed data accumulated over the last twenty-five years. We are also waiting for even more information to come from a great number of new and powerful Earth observation systems. Improvements on spatial and spectral resolution mean more gigabytes for a computer to manipulate. Hence, in order to explore all these sources of information, effective ways of fusing, analysing and storing this huge amount of data must be developed.

Digital change detection is also closely related to the issues mentioned above (Wong *et al.* 1997). For example, the combination of early images from Landsat MSS with upcoming data from Ikonos must be possible if we want to get the most from historical and up to date information. Analyses of dynamic processes with such a data set would provide useful inputs for historical characterisations, modelling and decision-making. The techniques available nowadays for detecting changes on rasterized data are extremely dependent on accurate radiometric and geometric rectification (Dai and Khorram 1998, Schott *et al.* 1988), which are very difficult tasks in some situations (e.g. poor quality of old sensors). The development of automatic analysis tools that could be able to minimise these requirements is recognised since the late eighties by Singh's classical review on change detection (Singh 1989).

Wavelet analysis provides a basis for handling multiresolution data sets, for understanding noisy signals and for improving storage efficiency. The technique is already recognised for remote sensing applications such as automatic image registration (Djamdji *et al.* 1993, Fonseca and Costa 1997, Fonseca *et al.* 1998), spatial and spectral fusion (Garguet-Duport *et al.* 1996, Blanc *et al.* 1998, Zhou *et al.* 1998), feature extraction (Simhadri *et al.* 1998), speckle reduction (Horgan 1998) and texture classification (Zhu and Yang 1998).

As far as the authors are aware the present contribution is the first attempt to derive a methodology, based on multiresolution wavelet analysis, for detecting changes on multidate satellite images with different radiometric and geometric characteristics.

2 MULTIRESOLUTION WAVELET ANALYSIS

Man-made sensors measure physical quantities and represent these as signals. In most cases the patterns shown by these signals are not clear and we try to transform them to extract information of interest. Wavelets are one of the many possible ways of transforming a given signal. The principle involved here is the representation of a vector (i.e. digital signal) by a linear combination of basis vectors (Unser 1996). The aim is to compare the signal at hand v with a set of test vectors v_i and their associated parameters b_i:

$$v = \sum b_i v_i . \tag{1}$$

In Fourier analysis we represent a given signal with a combination of sines or cosines as the basis, whereas in wavelet analysis this is done by dilated and translated versions of wavelets and scaling functions. For digitally sampled signals the output $y(n)$, representing the low frequency components, comes from the convolution of the signal at hand $x(n)$ with a lowpass filter h (scaling function), where k is a positional parameter for the filter coefficients and n is the time step:

$$y(n) = \sum_k h(k)\, x(n-k). \tag{2}$$

Then, the residual error between this lowpass filter at one level and its dilated version becomes the highpass filter g (wavelet function) which, after the convolution of the same input signal $x(n)$, produces the output $w(n)$, representing the high frequency components:

$$w(n) = \sum_k g(k)\, x(n-k). \tag{3}$$

At this point we have two new representations of the original signal: $y(n)$ and $w(n)$. One shows the low frequency components and the other the high frequency components that were mixed in one signal before. If we take the $y(n)$ and perform the same convolutions again we are moving to a coarser scale and representing this new input with a new set of basis vectors. This leads to a natural multiresolution representation of the original signal where the smooth part plus the details combine to form the signal at a finer scale level and so on.

The capacity of perceiving scales can be the key for better understanding the signals around like complex biological sensors do. Our eyes, for instance, evaluate the overall picture and afterwards see the details. Remotely sensed images are two-dimensional signals which are relatively noisy and provide lots of information at different spatial scales. In this context, their analysis can be considerably improved if their transformations show detailed and overall views. Multiresolution wavelet analysis in discrete time corresponds to successive band pass filters decomposing the signal at each step into details and overall pattern. In a two-channel filter bank (Figure 1) it separates the high from the low frequencies recursively using the same transform at a new scale (Strang and Nguyen 1997).

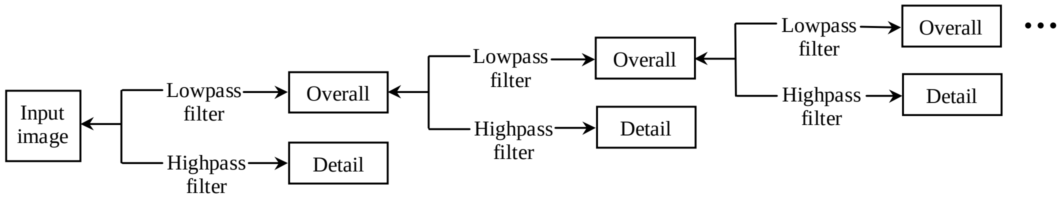


Figure 1. Wavelet tree.

Two algorithms will be used to implement this filter bank. The first follows a pyramidal scheme where only one sample out of two is kept after the filtering process (i. e. downsampling) (Burt and Adelson, 1983). The resolution decreases by a factor of two at each decomposition level. No information is lost by this procedure and perfect reconstruction of the original signal is still possible as long as the chosen filters allow it. Pyramidal transforms are particularly useful for data compression as well as for resolution reduction.

The second is known as the *à trous* algorithm (Holschneider *et al.* 1989) where all output samples are kept. This means redundancy as we could have ignored samples without losing information. Even then, for remote sensing applications this redundancy can be of much use. One drawback is that after each decomposition level we double the memory required for storage. On the other hand, feature extraction is improved by this kind of algorithm.

3 STUDY SITE AND DATA

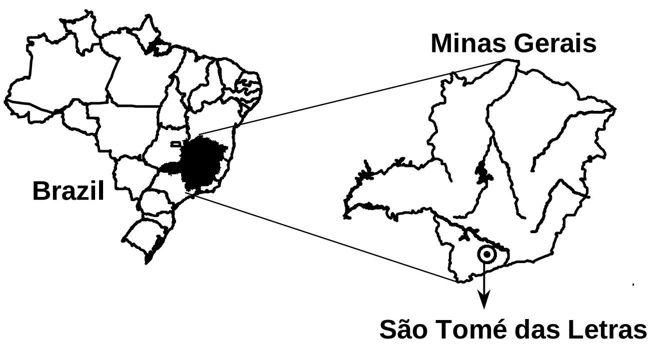
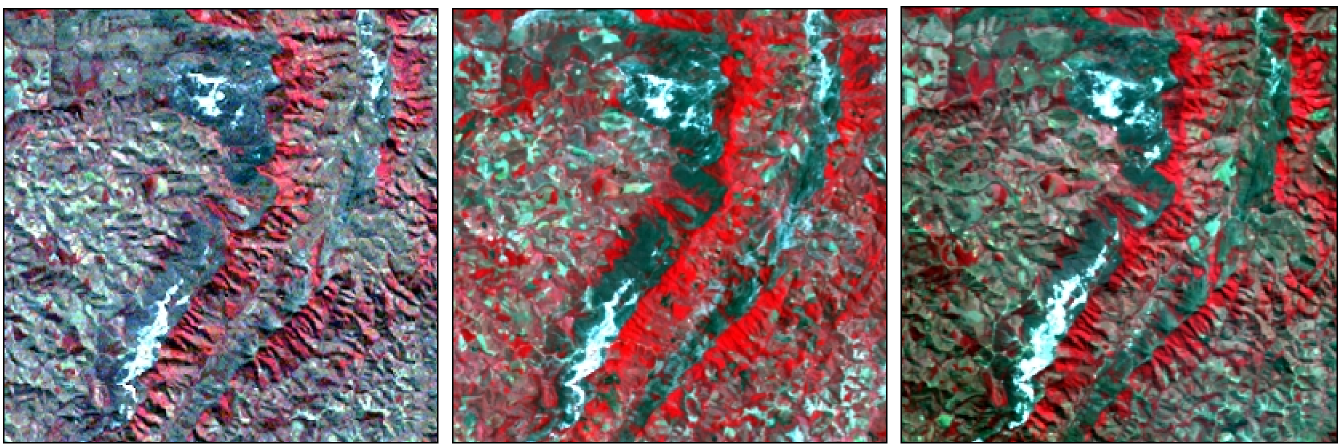


Figure 2. Location of the Study Site.

An area around the city of São Tomé das Letras in the state of Minas Gerais, south-eastern Brazil, was chosen as case study (Figure 2). The site is used for agriculture, rock exploitation and for the protection of remnants of cerrado (Brazilian savanna), rocky fields and semi-deciduous Atlantic forests. Climate is Cwb (Köpen's classification), characterised by dry winter and wet summers. In the last 20 years there was an increase of mining activities and losses of forest cover among periodic changes due to agricultural activities. South-eastern Brazil is the most populated region of the country. Pressure over natural resources has been very intense since the last century resulting on a highly fragmented area.

One Landsat MSS image from July 1981 and two Landsat TM images from November 1985 and August 1998 were used in this research. Each pixel of the Landsat TM and MSS images covers a ground area of about 900m^2 and 3600m^2 respectively. Landsat TM bands 2 (520-600 nm), 3 (630-690 nm), 4 (760-900 nm) and Landsat MSS bands 1 (500-590 nm), 2 (610-680 nm), 3 (790-890 nm) were chosen to perform this experiment because they cover comparable portions of the electromagnetic spectrum (Buiten and Clevers 1996). In addition, also phenological conditions are different within this data set (Figure 3).
Ancillary data comprised aerial photographs from 1979 and 1984 as well as field visits during the summer of 1999.



(a) (b) (c)

Figure 3. Landsat MSS from 1981 (a) bands 321 in RGB. Landsat TM from 1985 (b) and from 1998 (c) bands 432 in RGB reduced to 60 m of ground resolution. Using this colour combination forest areas appear in red tones while mining sites appear in white.

4 WAVELET BASED CHANGE DETECTION

To be able to digitally detect changes on images acquired by different sensors we need first to bring all images to the same ground resolution. This was achieved by applying a one level pyramidal wavelet algorithm to the Landsat TM image from 1998 using as the scaling function a cubic spline (Starck *et al.* 1998). The resolution decreases by a factor of two after each decomposition level. Hence, the pixel size for the Landsat TM images became 60x60m after the transformation. Landsat MSS images were already acquired with a ground resolution of 57x57m and reduced to 60x60m by a simple nearest neighbour resampling procedure. The Landsat TM images from 1985 and from 1998 were also processed at the original ground resolution of 30x30m.

Ten ground control points were visually selected at corresponding locations on both images to perform geometric registration. The deformation model used was a polynomial of first degree and a nearest neighbour resampling created the warped image. No radiometric rectification was applied to the input images and the spatial misregistration (RMS error < 1 pixel) ranged from one to three pixels when visually evaluated.

All images were then individually decomposed into five levels by the ‘à trous’ algorithm (Starck *et al.* 1998). Again, a cubic spline was used as the low pass filter and the difference between the scaling function at one level and a dilated version of the same function became the high pass filter. Finally, subtracting corresponding wavelet images we end up with the equivalent of decomposing the difference image. At this point the differences between the images are separated into five detail levels ranging from fine to coarse and a smoothed representation of the original difference image (Figure 4).

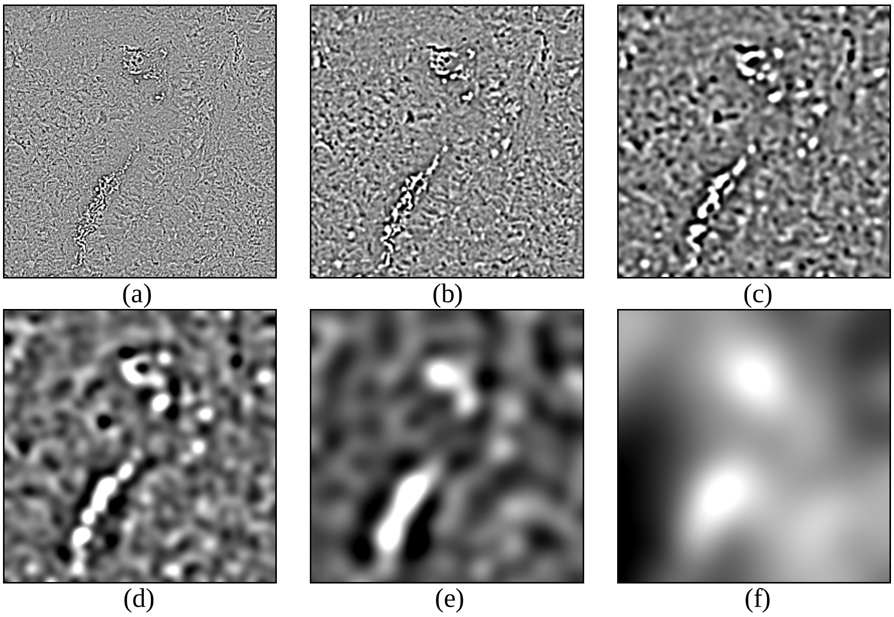


Figure 4. Detail images ranging from fine to coarse (a, b, c, d and e) and smoothed version (f) of the difference between 1998 (TM band 3) and 1981 (MSS band 2) decomposed using the *à trous* algorithm.

In order to detect deforestation and new mining areas we multiplied details at the second scale by the details at the third scale when comparing images of 60x60m of ground resolution, hereafter called changes of interest. The product of wavelet scales is analysed in Sandler and Swami (1999) as a means of enhancing important transitions in the data. For images of 30x30m of ground resolution we used details at third and fourth scale levels. This product acts as an enhancement technique to further separate meaningful information from noise. It also combines in one image size classes from different scale levels. Depending on the types of changes under investigation other scale levels could be combined or even analysed alone.

Image processing was carried out in ENVI, The Environment for Visualising Images (ENVI, 1997) except for the wavelet transforms that were performed in the MR/1, Multiresolution Analysis Software (MR/1, 1999).

5 EXPERIMENTAL RESULTS

By multiplying the wavelet images, all directions of changes get positive values. Visualisation can be readily done with a simple colour composite. To visualise changes from dark to light (e.g. deforestation in TM band 5), one must use the oldest image to make the composite (Figure 5). Changes from light to dark (e.g. reforestation in TM band 5) are better visualised when using the most recent image. This is because the background at sites where changes are to be visualised must be dark so that the changes of interest could be emphasised. Ground-truth for changed areas was acquired during field trips in 1999 and from interpretation of aerial photographs from 1979 and 1984. All changes detected by this visualisation procedure did occur although their quantification was not possible. Note that in Figure 5 the whole triangular forest fragment at the bottom right disappeared between 1985 and 1998 although only its centre is being enhanced.

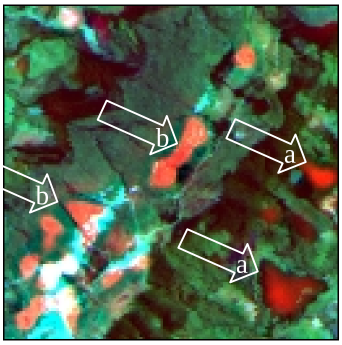


Figure 5. Landsat TM from 1985. Changes of interest coloured with red, band 4 with green and band 3 with blue. Arrows indicate areas where (a) deforestation and (b) mining increased.

In the 3D graphs of Figure 6 note that lots of unimportant information that could be considered noise does not appear in the change image built with the combination of wavelet images (Figure 6b). This ‘cleaning’ effect makes the analysis and understanding of remotely sensed images or outputs from image processing much easier.

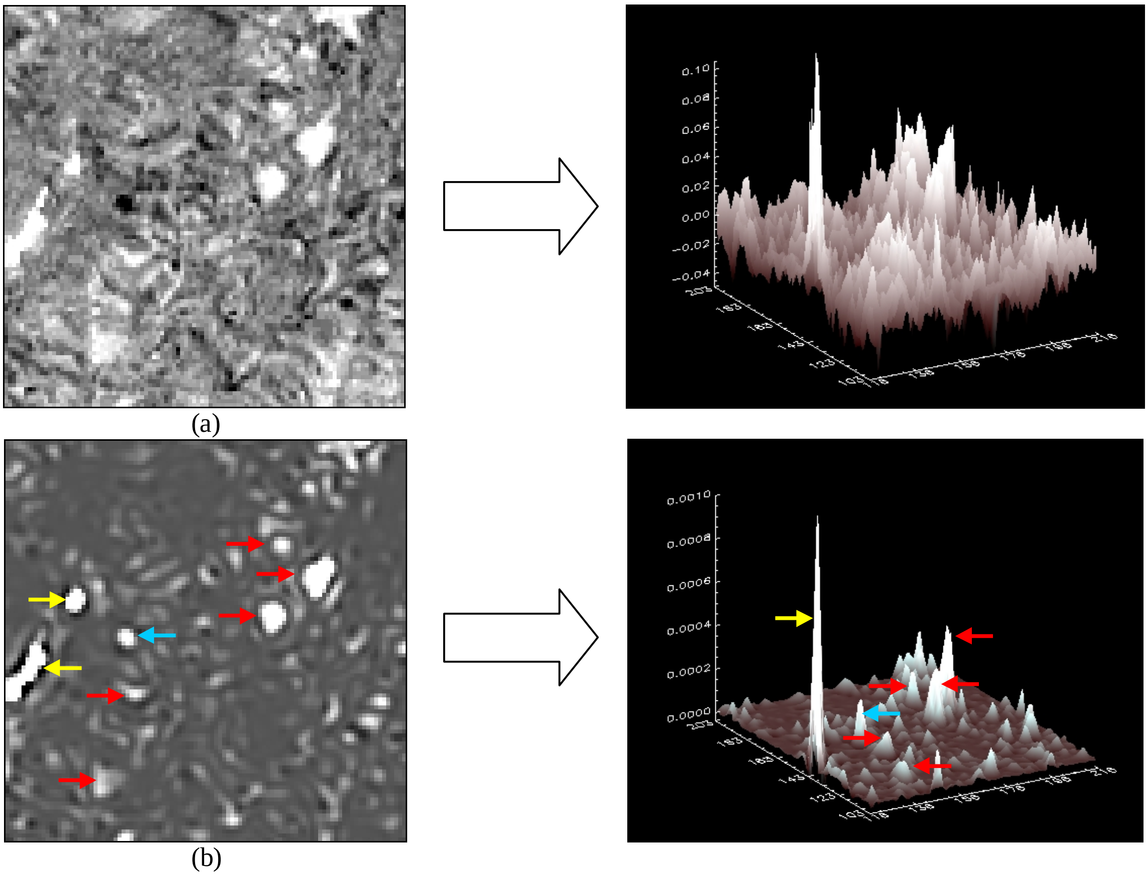


Figure 6. (a) Difference image between band 3 of Lansat TM from 1998 and band 2 of Landsat MSS from 1981 with respective magnitude graph. (b) Product of differences at second and third scales and respective magnitude graph.

Deforested areas (red arrows), reforested areas (blue arrows) as well as new mining sites (yellow arrows) were successfully pinpointed in Figure 6b without previous radiometric rectification or threshold definition while differences not related to land cover changes were bypassed. Verification was done by visual evaluation of ancillary data.

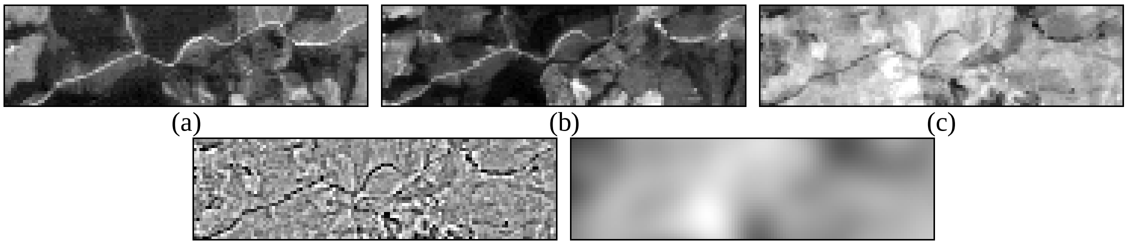


Figure 7. Lansat TM from (a) 1998 and (b) 1985 and (c) respective difference image. (d) Details of the difference image at the first scale level. (e) Smoothed version of the difference image at the fourth scale level. Note the misregistered road depicted in (d) while overall differences like phenological condition of vegetation patches are depicted in (e).

6 DISCUSSION

The behaviour of changes at different scale levels enables their discrimination according to size classes. Misregistration effects and small area changes are depicted as fine details (Figure 7d). Phenological characteristics, atmospheric effects and differences in sensor calibration appear in the smooth representation of the signal (Figure 7e). Hence, using information from intermediate scale levels one can minimise the problems mentioned above. We found the method less sensitive to spatial and radiometric misregistration, although fine details are lost as well. It can be applied to the outputs of any change detection technique such as image rationing, principal components, change vector analysis etc.

Further statistical analysis could also be applied to the wavelet frames but these procedures would be analogous to thresholding operations (Ruttimann 1996). The selection of scales to discard and of significant coefficients to keep could be driven by statistical tests if no knowledge exists on the size of features of interest.

Changes are well discriminated but their quantification is not possible when using information from limited scale levels. Further research on the combination with other techniques, like region growing algorithms, could be a solution for area determination. Applications of the proposed method include, for instance, the automatic selection of changed sites for GIS updating. Finally, with respect to geo-information for all, the visualisation of changed sites can be done straightforwardly with a simple colour composite avoiding any threshold definition and easily implemented by non-experts in image processing.

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