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► To cite this version:

Sonia Bouzidi, Isabelle Herlin, Ahmed Habbani. An approach using low resolution remote sensing data to detect land cover changes. ISESS: International Symposium on Environmental Software Systems, May 2003, Semmering, Austria. 2003. <inria-00527190>

HAL Id: inria-00527190

<https://hal.inria.fr/inria-00527190>

Submitted on 18 Oct 2016

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An approach using low resolution remote sensing data to detect land cover changes

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Abstract

The paper addresses land cover monitoring at large scale. It investigates an approach for extracting information from remote sensing data and evaluating the possibility of doing automated analysis to detect land use changes. A multi-resolution remote sensing data process is performed to obtain curves describing the temporal reflectance profiles related to land cover behaviour. Then a time-frequency transformation is used to extract relevant features characterizing these profiles. The features are then projected on a representation space improving discrimination between different land cover types. This approach can be applied in a scenario dedicated to the detection of land use changes caused by erosion.

1. Introduction

Monitoring land cover activities is needed to better evaluate the changes occurred and hence to control the effects of environmental degradation. The classical methodology for studying land cover changes is based on using empirical means such as videography, ground truthing. But it requires a considerable interaction with an expert in photo-interpretation and it cannot be applied on large areas. Remote sensing provides data at different spatial and temporal resolutions that can be used to improve environment monitoring. Land cover monitoring can be performed with a high temporal frequency by using sensors such as NOAA/AVHRR or VEGETATION which offer a synoptic view and multi-spectral information. However, due to the spatial resolution (about 1km at nadir), the measurement is global and cannot be linked to a specific type of land cover. To overcome this limitation, we define a process making it possible the access to individual information related to each land cover type. The proposed process is based on NOAA pixels decomposition with a linear mixture modelling for visible and near infra-red channels. This process allows the computation of temporal profiles of reflectance related to the behaviour of each land cover under study. Computation is performed locally: we then obtain a set of curves for each land cover type by varying the spatial location. Using a training set of the obtained curves, we perform a learning process to extract relevant features for land cover types characterization. We aim to project these features onto a representation space where the discrimination between land cover classes (groups of curves related to each land cover type) is easier than in the initial time domain.

These representation can be used to detect changes, in fact, local deviation from a standard profile should be interpreted. The paper is organized as follows: In section 2, we describe the process of curves determination from remote sensing data. Section 3 describes the developed approach with the different steps: curves coding using DWT (subsection 3.1) feature extraction (subsection 3.2), discussion of the representation space choice and the classification method (subsection 3.3). In section 4, we discuss the obtained results. The section 5 is devoted to describe the perspective of applying this work in land cover changes detection. Finally we conclude and present future work in section 6.

2. Curves determination

Identifying and monitoring land cover components is depending on spatial resolution and temporal frequency of observations. High spatial resolution data provided by Landsat TM or SPOT improved with ground truthing give a good information about land cover. However, it is too difficult and very expensive to frequently obtain this kind of data for important surfaces. To study progressive phenomena, we can exploit NOAA/AVHRR sensors which provide daily acquisitions covering large areas. Nevertheless, due to the size of a pixel (1.1 km), which is generally larger than a single field, monitoring vegetation with NOAA/AVHRR data implies a mixture modeling for pixels values. We assume a linear model (1) where the reflectance of a pixel is considered as a sum of the individual land covers reflectances weighted by their area proportions [Quarmby & al]. This relation is considered in the visible and Near InfraRed channels:

$$r_i^k(t) = \sum_{j=1}^C \rho_{ij} R_j^{k(loc_i)}(t) \quad (k=1,2) \quad (1)$$

where:

- C is the number of land cover types,
- $r_i^k(t)$ the reflectance of a NOAA pixel i in channel k ($k = 1$ or 2), at date t .
- $R_j^{k(loc_i)}(t)$ the individual reflectance of land cover type j computed locally around the pixel i in channel k ($k = 1$ or 2), at date t .
- ρ_{ij} the proportion of the land cover j within a NOAA pixel i .

We consider an area for which ground truth and remote sensing data are simultaneously available. So that a precise land cover thematic classification is obtained for this area at high spatial resolution (of Landsat). Then, after geometrical registration, we superpose the Landsat classification image and the NOAA images [Bouzidi & al]. Consequently, for each NOAA pixel, its composition in terms of percentage of land cover can be obtained by directly counting pixels on the Landsat classification image. We then obtain the ρ_{ij} values for the studied area.

At each date t , for each pixel i , we consider its neighbors. The neighborhood size is depending on the number of land cover types, in our case we consider 8 neighbors of a pixel i . So we obtain a linear system of 9 equations. The $r_i^k(t)$ are observed on the NOAA sequence of images; knowing the ρ_{ij} , the inversion of the linear system allows the estimation of individual values for this date. By repeating this process for all the dates, the temporal profiles $R_j^{k(loc_i)}(t)$ are computed. So that for each land cover type j and for each NOAA channel (1 and 2), we obtain as many curves as considered NOAA pixels.

3. Curves Characterization

Time-frequency transformation has proved its efficiency for non stationary signals analysis in different application fields such as : speech analysis [Yang & al][Kronland & al], biomedical engineering [Englehart & al], imagery [Mallat & al], One of the most used techniques to perform signal transformation is the Wavelet Transform and more particularly Discrete Wavelet Transform (DWT) which filters noise and provides a compact representation of a signal making it easier the extraction of information [Intrator]. This work investigates another application area of time-frequency transformation. It addresses the use of this technique in order to characterize the curves describing the temporal reflectance profiles related to land cover behaviour and obtained as explained in section 2. These curves represent reflectance evolution in function of time (day of the year) in the visible and Near-Infrared (NIR) channels of NOAA/AVHRR sensor. We aim to project these curves onto a feature space where classes of land cover will be better discriminated. To achieve curves classification the approach illustrated in figure 1 is followed. The first stage is the signal representation which consists on applying a Discrete Wavelet Transform in order to denoise the signal then a feature extraction to characterize it. The second stage is the classification of the feature vectors.

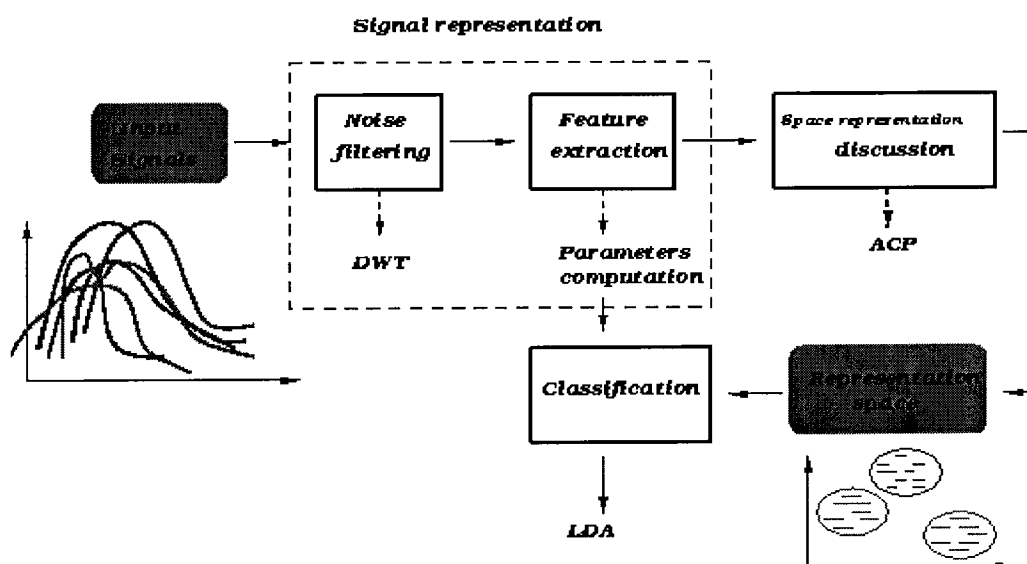


Figure 1 : the global approach scheme

3.1 Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) provides a time-frequency representation of a signal. It transforms a time domain discretized signal $x(n)$ of finite length $\{1, \dots, 2^N\}$ into its corresponding wavelet domain. This is done through a process called "sub-band codification" which is done through digital filter techniques. It allows the signal decomposition into an approximation and detail information. The approximation is then further decomposed using the same wavelet decomposition transform. This is achieved by successive high-pass and low-pass filtering of the time domain signal and is defined by the following equations:

$$Y_{\text{high}}[k] = \sum_n x[n]g[2k-n] \quad (2)$$

$$Y_{low}[k] = \sum_n x[n]h[2k-n] \quad (3)$$

Where $Y_{high}[k]$, $Y_{low}[k]$ are respectively the outputs of the high-pass (g) and low-pass (h) filters, after subsampling by 2. A set of different wavelet families have been proposed in the literature. In our implementation, the four coefficients wavelet family (DAUB 4) proposed by [Daubechies] is used.

3.2. Feature extraction

After performing the DWT, statistics over the set of wavelet coefficients are used. We compute different parameters to study the profiles features:

- the mean of the absolute values of the coefficients in each sub-band. These features provide information about the reflectance distribution;
- the standard deviation in each sub-band, this provides information about variation in the frequency distribution.
- the maximal and the minimal values and their positions in the approximation sub-bands. These features allow a time-scale localization and provide information about the curves shape.

The observation and comparison of these parameters in the different sub-bands at each decomposition level allow the choice of the more significant parameters as well as the decomposition level supposed sufficient for the signal representation without losing information. Since each profile is described by two curves in the visible (channel1 of NOAA/AVHRR) and in the Near Infrared (channel 2 of NOAA/AVHRR), feature extraction is performed in the two channels. So that each land cover profile is characterized by the parameters previously described and computed in the two NOAA channels.

3.3. Classification and representation space

The data (Temporal profiles) are divided into a training set and a test set. The training set is used to define the classes and to choose the representation space. The test set is used to evaluate the classification performance.

Let N be the number of training profiles (x_i^k, c) ; for each land cover class c ; $c = 1, \dots, C$ where C is the number of land cover types, $i = 1, \dots, N$; $k = 1$ and 2 (NOAA channels). For each profile (x_i^1, x_i^2, c) , we compute the feature vector as it is described in the subsection 2.2, then we perform classes definition. Two representation spaces are discussed:

- The first one consists in applying Principal Components Analysis (PCA) in order to reduce dimensionality and to produce an uncorrelated feature set. Hence, the feature vectors are projected on the principal components space where classes are defined. In this new space, a Linear Discriminant Analysis (LDA) is applied. It is a linear statistic classification method which maximizes the ratio of between class variance to the within class variance in order to obtain decision regions between the different classes of data. It is a question of finding linear transform A , so that after its application the scatter of sample vectors is minimized within each class and the scatter of mean vectors around the total mean vector is maximized simultaneously.
- The second case consists in applying LDA directly in the space of the original features (without PCA application). In our case, this allows us to test the relevance of reducing

dimensionality by PCA and to evaluate its effect on the LDA performance.

3.3.1 Classification method description

The classification step is based on defining a criterion to assign a temporal profile of reflectance, described by its features vector, to a class of land cover. Each class c is defined by its mean vector .

$$X_c = \frac{1}{N} \sum_{i=1}^N X_{i,c} \quad (4)$$

where $X_{i,c}$ is the original feature vector or its projection on the principal component space after a PCA application.

The within class variance is estimated by the covariance Matrix (5)

$$S_w = \sum_{c=1}^C \frac{1}{C} \sum_{i=1}^N \frac{1}{N} (X_{i,c} - X_c)(X_{i,c} - X_c)^T \quad (5)$$

The between class variance is (6):

$$S_b = \sum_{c=1}^C \frac{1}{C} (X_c - X)(X_c - X)^T \quad (6)$$

Where

$$X = \sum_{c=1}^C \frac{1}{C} X_c$$

The maximization of the ratio $\frac{S_b}{S_w}$ allows the determination of the linear transformation A improving classes discrimination. A new temporal profile of reflectance (or a temporal profile from the test set) Y is assigned to the class for which $d(A^T Y; A^T X_c)$ is minimal, with d the euclidian distance.

4. Experimental results and discussion

The developed approach has been applied on a test area of the Mkomazi basin in South Africa. The thematic classification obtained for this region at Landsat resolution presents four classes of land cover: water, grass, forest and bare soil. We first produce temporal profiles of reflectance at it is previously explained. The figures 2 and 3 represent an example of results obtained for grass. They show a set of curves obtained by varying spatial location.

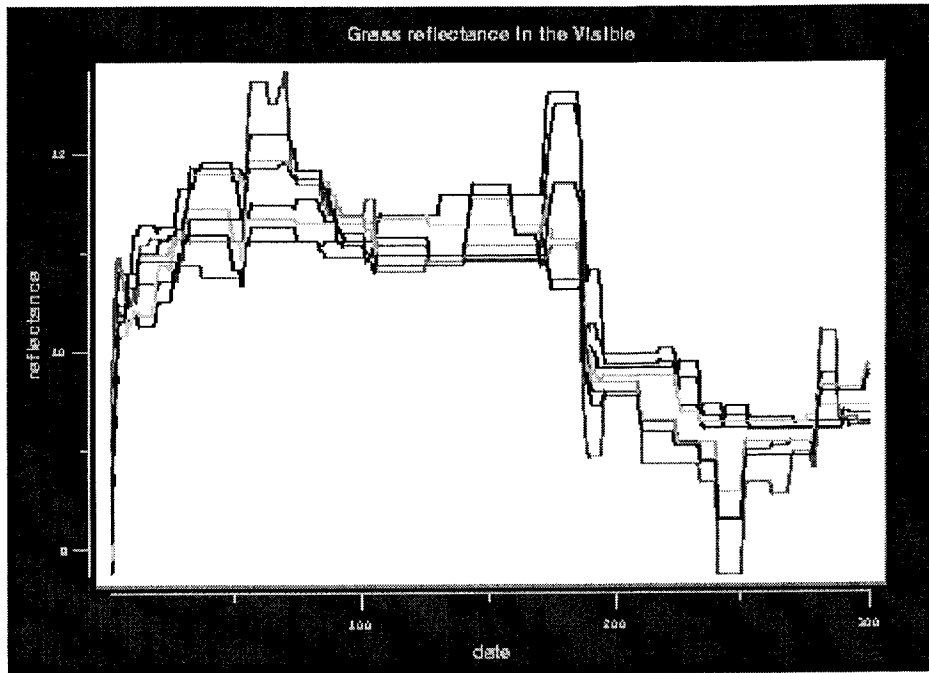


Figure 2 : Examples of curves of reflectance in the visible (grass).

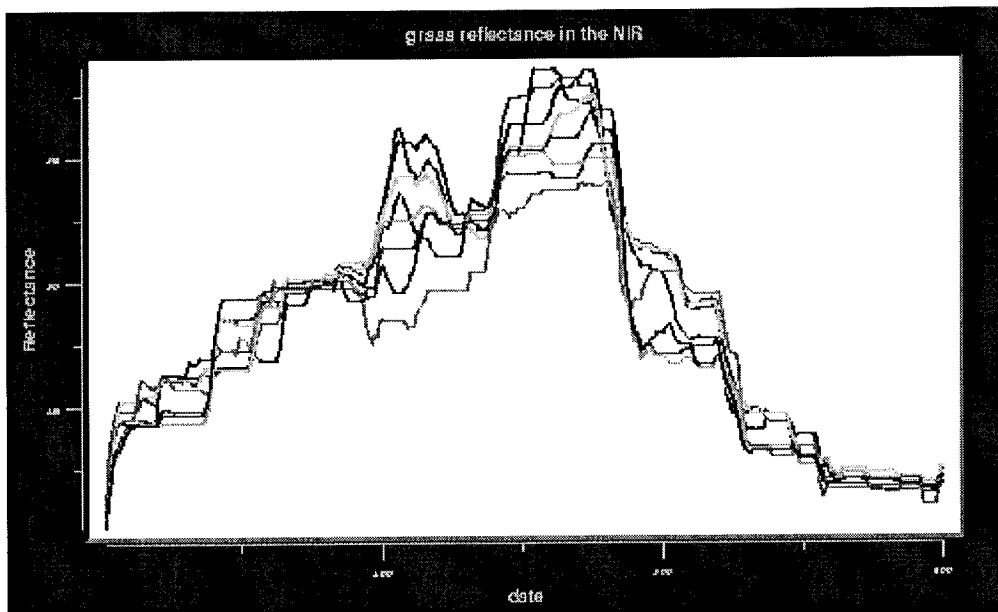


Figure 3 : Examples of curves of reflectance in the Near InfraRed (grass).

The second step is wavelet transformation and features extraction for curves coding. Among the computed curves we have chosen training samples (100 profiles) and validation samples (150 profiles). The training set is used to classes definition and the other set for evaluating the classification performance.

The classification method LDA has been applied into two spaces: the Principal Components space and the original features space. The table 1 presents the classification accuracy (on the test samples) for each land cover type:

| Class | PCA and LDA | LDA |
|-----------|-------------|-----|
| Grass | 85% | 87% |
| bare soil | 61% | 62% |
| Forest | 52% | 55% |
| Water | 90% | 92% |

Table 1: Classification results.

We notice that we have better classification accuracy when applying LDA on the original feature vectors. Both LDA and PCA project the original feature vectors onto a new space through a transformation. The PCA changes both the location and the shape of the data in its transformed space whereas LDA only provides more class separability by building a decision between the classes. Obtaining a decrease of classification accuracy by PCA application before LDA can be explained by a loss of information after the first transformation. The confusion matrix presented in table 2 gives more details about classification results.

| | Grass | forest | Bare soil | water |
|-----------|-------|--------|-----------|-------|
| Grass | 87% | 0% | 13% | 0% |
| Forest | 8% | 55% | 21% | 16% |
| bare soil | 13% | 24% | 62% | 1% |
| Water | 0% | 8% | 0% | 92% |

Table 2 :Confusion matrix.

It shows an important confusion between bare soil and forest. The reasons of this confusion can be investigated at two levels:

- 1- firstly, at the learning step: the training samples have to be carefully chosen, in such a way that they actually represent the land cover classes. In fact forest is a mixture of bare soil and trees, if we have a low density of trees the reflectance can be very close to that of bare soil.
- 2- secondly, at the feature extraction step: more relevant features to discriminate curves can be investigated in order to improve classification performance.

5. Example of an application scenario to land cover changes detection

The representation space obtained from the learning step can be used in an operational context in order to detect land cover changes. The proposed framework is illustrated in figure 4.

For a given site, we consider a year of reference for which we apply the approach described in section 2 to obtain the representation space of the land cover classes.

The next NOAA/AVHRR sequences provided after the reference year are used to estimate the new profiles for the land cover types of the same area. The obtained curves are then processed to extract relevant features then projected onto the representation space corresponding to the reference year. Two different cases are possible for a profile representing locally a given land cover type:

- 1- The new profile is assigned to the corresponding land cover class. For example a profile assumed to be grass is classified as grass in the reference space. This implies that there is no change.

- 2- The new profile is closer to another land cover class. This implies that there is change and it has to be interpreted. For example a profile which is assumed to be grass is closer to the class representing bare soil. This may be interpreted by an erosion process occurring in the localization where the profile is obtained.

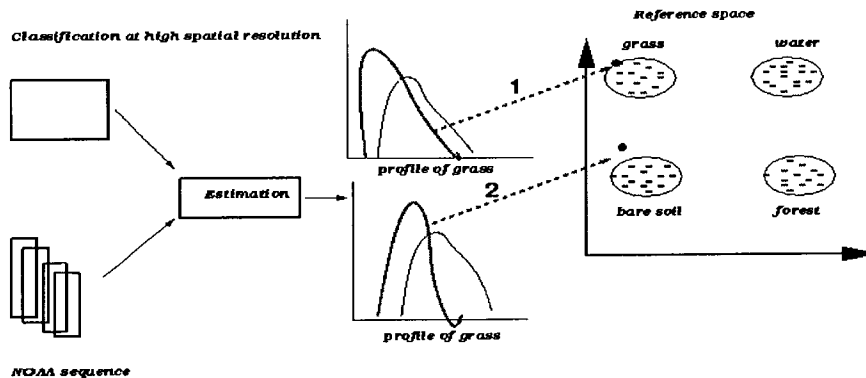


figure 4: Change detection scenario.

6. Conclusion and perspectives

The work presented in this paper deals with a new application of signals classification. It describes an approach to characterize land cover types from their temporal profiles of reflectance and then to project them onto a feature space maximizing discrimination between land cover classes. The first obtained results are promising and we are investigating different ways to improve them. Improvements of classification accuracy can be expected by more careful experimentations to choose features for characterizing curves. We are studying parameters more relevant for the shape information such as the local extrema. We also plan to investigate the use of other wavelet families. Moreover, we are studying the method of wavelet optimization for classification proposed in [Flucas & al]. It is an approach which allows the determination of the mother wavelet yielding the best classification result. It is realized by optimizing the filter coefficients according to a contrast criterion calculated on the learning set. An other way to improve classes discrimination proposed in [Saito & al] and [Coifman & al] can be also investigated on our data. It is a method to construct an orthonormal basis which maximize classes separability. The results of the classification process is a reference space which can be used in an operational context making it possible the detection of land cover changes at early stage.

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