TEMPORAL ANALYSIS OF MULTISENSOR DATA FOR FOREST CHANGE DETECTION USING HIDDEN MARKOV MODELS

Arnt-Børre Salberg and Øivind Due Trier

Norwegian Computing Center
Dept. SAMBA, Section for Earth Observation
P.O. Box 114 Blindern, NO-0314 Oslo, Norway

ABSTRACT

Remote sensing plays a key role in monitoring the quality and coverage of the tropical forests, and for early warning of illegal logging and forest degradation. We propose a hidden Markov model based framework for analyzing multi-source time series of remote sensing images of tropical forests with the aim of detecting changes in the spatial coverage of the forest. Multi-source is supported by the hidden Markov model by applying specific data distributions for each source. The proposed methodology is demonstrated on a time series of Landsat TM and Radarsat-2 quad-pol images covering tropical forest in Tanzania. The results are evaluated by visual inspection of Landsat 5 TM images.

1. INTRODUCTION

The tropical forest is a key component for a sustainable climate and a rich biodiversity on Earth. Several initiatives have been established to support countries with strategies to reduce emissions from deforestation and forest degradation. Earth observation systems play a key role in monitoring the quality and coverage of the tropical forests, and for early warning of illegal logging.

In this context, change detection refers to the problem of detecting deforestation and forest degradation in images of some area on the ground taken at different time instants. Attempts at doing forest change detection from two single land cover maps of the same area at two different dates is less reliable, as the errors from the two classifications add up. Rather, a time series of many acquisitions of each scene is needed to account for the inherent variability due to seasonal (phenological) variations of ground cover reflectance, varying atmospheric disturbances, missing data due to cloud cover, humidity on the ground, etc.

Due to the high frequency of clouds in many tropical forests, a time-series of optical images may contain too few observations of the ground vegetation for reliable change detection. This calls for the use of SAR sensors, which can see through all but the thickest clouds. However, SAR images may be more difficult to interpret than optical images, both for humans and automatic processing methods. One solution could be to combine optical and SAR images in a multisensor time series analysis.

Hidden Markov models (HMM) have been applied with promising results as a means for analyzing time series of images in remote sensing, in particular for modeling vegetation dynamics and phenological variations [1, 2, 3]. In this paper we extend the HMM approach for multi-temporal optical images [3] to consider a time series of multisensor images (optical and radar images), and we model each pixel in the time series of multisensor images using a HMM (Fig. 1). By considering the states forest and not-forest, tree cover products maybe produced more accurately by allowing for the modeling of natural variation of the land cover and noise. Moreover, robust change detection may be obtained from two subsequent state estimates, since the state sequence is estimated by considering the time series of images, and not pairs of classified single images.

2. TEMPORAL FOREST COVER SEQUENCE

A HMM is used to model each location on the ground as being in one of the following states $\omega = \{\textit{forest}, \textit{sparse forest}, \textit{grass}, \textit{soil}\}$. The term "hidden" refers to the fact that the true land cover is not known. However, we have observations, in the form of image data for each pixel area on ground. These observations are used by the multisensor time series analysis to predict the sequence of states for each pixel on ground. Since a HMM propagates probabilities from one state to the next, it naturally supports multisensor data as long as we are able to express the class conditional data distributions. To allow for the use of optical images with partial cloud coverage, the cloud covered parts will be modeled as "missing observations" (as illustrated in Fig. 1). SAR image pixels that are distorted by layover and shadow effects are also labeled as missing.

Assume that the state transition between two time-instants $t-1$ and t is modeled using a Markov chain model $P(\omega_t \mid \omega_{t-1})$. Let $\mathbf{x}_t$ denote a vector containing the observed features (in this work the features are optical brightness or SAR backscatter intensity values) of a given pixel at time-instant t. Further, let $\mathcal{X} \subseteq \mathcal{X}_i^N = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$ and $\Omega = \{\omega_1, \omega_2, \ldots, \omega_N\}$ denote a set of observed feature vectors (some feature vectors may be missing due to clouds) and states, respectively, for all times-instants $1, 2, \ldots, N$. The Bayes rule for Markovian models may then be expressed as

$$p(\mathcal{X}, \Omega) = p(\mathcal{X} \mid \Omega) P(\Omega) = \prod_{t=1}^{N} P(\omega_t \mid \omega_{t-1}) \cdot \prod_{t \in \mathcal{I}_o} p(\mathbf{x}_t \mid \omega_t). \tag{1}$$

where $P(\omega_1 \mid \omega_0) = P(\omega_1)$, $p(\mathbf{x}_t \mid \omega_t)$ is the class conditional data distribution, and $\mathcal{I}_o \subseteq \{1, \ldots, N\}$ denotes the set of indices where $\mathbf{x}_t$ is observed.

According to the maximum likelihood state sequence criterion we compute the most probable (best), or maximum likelihood (ML), sequences of states, given the observed data $\mathcal{X}$. This sequence is found by computing the maximum of $\log p(\mathcal{X}, \Omega)$, i.e.

$$\{\widehat{\omega}_1, \ldots, \widehat{\omega}_N\} = \arg \max_{\omega_1, \omega_2, \ldots, \omega_N} \Big[\sum_{t=1}^{N} \log P(\omega_t \mid \omega_{t-1}) + \sum_{t \in \mathcal{I}_o} \log p(\mathbf{x}_t \mid \omega_t) \Big]. \tag{2}$$

Since the ML criterion jointly estimates the whole sequence of states, it does not propagate classification errors from one time instant to the next, and is therefore a recommended method when using the hidden Markov model in change detection applications [3]. The ML state sequence may be found efficiently using the Viterbi-algorithm [4]

The state transition probability $P(\omega_t | \omega_{t-1})$ defines the prior probability of going from state ω_{t-1} at time instant $t-1$ to state ω_t at time instant t. These probabilities depend strongly on the application under investigation, and may be estimated from the data [5]. Let $P_0(\omega_t = m | \omega_{t-1} = m') = P_0(m|m')$ denote the *basis* transition probability from state m' to state m corresponding to *two* subsequent days. Then by integrating out state variables in the interval not considered, the state transition probability for a given time interval Δ_t days may be expressed as

$$\mathbf{P}_t = \prod_{t=1}^{\Delta_t} \mathbf{P}_0 = \mathbf{P}_0^{\Delta_t}. \tag{3}$$

where the element at column m and row m' of the transition probability matrix $\mathbf{P}_0$ is equal to $P_0(m|m')$.

In general, then data distributions $p(\mathbf{x}_t|\omega_t)$ may change between the time instans, i.e $p(\mathbf{x}_t|\omega_t) = p_t(\mathbf{x}_t|\omega_t)$ due to atmospherical, phenological variarions , and/or when the sensor is changing.

3. EXPERIMENTS - LANDSAT AND RADARSAT-2 QUAD-POL IMAGES OF TROPICAL FOREST

We now demonstrate the proposed multisensor time series analysis methodology to a time series consiting of 4 Landsat 5 TM images from path/row 166/67 (1986-05-15, 1991-05-29, 1992-07-02 and 1993-05-15) and a Radarsat-2 quad-pol image from 2010-03-19 (product id. 00963600) covering an area north in the Liwale region in Tanzania. For the Landsat observations we use bands 2-5 and 7 as features, and for the Radarsat-2 observations we use the Pauli-decomposition $|S_{HH} + S_{VV}|^2$, $|S_{HH} - S_{VV}|^2$ and $|S_{VH}|^2$. The resolution of the SAR image is reduced to the resolution of the Landsat images by multilooking. Geocoding of the SAR image is based on the 30m ASTER Global Digital Elevation Model (downloaded from USGS LP DAAC Global Data Explorer).

Cloud/shadow detection in the Landsat images is performed using the method proposed by Salberg [6]. Since

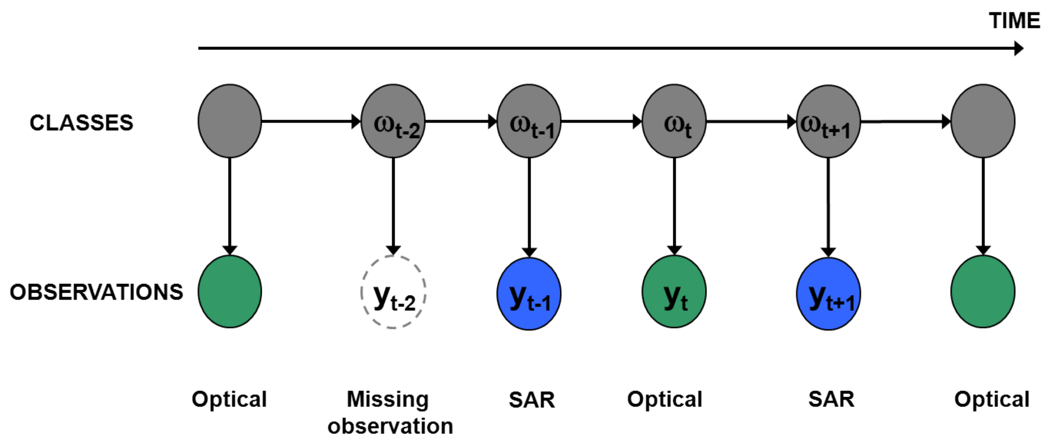

Fig. 1: Principle of the multisensor hidden Markov model. Each pixel has a corresponding time series of hidden states, and each state may or may not have an associated observation. The hidden states are in grey, the optical observations are in green, the SAR observations are in blue, and the missing observations are indicated as dashed circles.

cloud and cloud shadows are visually easily distinguished from vegetation, soil, etc, we assume that this classification task may be achieved with very high accuracy. Landsat pixels classified as clouds or cloud shadows are labeled as missing.

The state transition probabilities need to be determined before we can classify the time series. In this work we have selected fixed values of the basis transition probability matrix $\mathbf{P}_0$ (alternatively may this be estimated from the data).

We model the optical data using a multivariate Gaussian distribution, whose mean vector and covariance matrix are estimated from the training data corresponding to the classes *forest*, *sparse forest*, *grass*, and *soil*, extracted from two different Landsat 5 TM images (path/row 166/63) acquired on the 2010-02-01 and 1986-10-06. To account for brightness variations (atmospheric distortions) between the Landsat images in the time series, we apply the method suggest by Salberg [6] to adjust the parameters of the class dependent data distributions. This method estimates the mean vector of a given class as a weighted average of the class mean vectors estimated from the training images. The covariance matrix is estimated similarly, but without weighting. The values of the Pauli-decomposition of the SAR data is also modeled using a Gaussian distribution, and the class dependent mean vectors and covariance matrices are estimated from training data extracted from a Radarasat-2 quad-pol image covering an area north in the Tanga Region.

4. RESULTS

The HMM-based multisensor time-series analysis extracted the class sequence corresponding to each pixel, and from that sequence change detection maps for each time-instant were created (Fig. 2). In the SAR image we observe terrain effects (due to variations in terrain elevation). From the change-detection map we noticed that we were able to detect changes in land cover when to subsequent images were acquired by different sensors. We further noticed that few areas were exposed to reduction of forest cover from 1986 to 2010 (Fig. 2(lower right)). No areas showed a growth in forest cover, however, this may be due to the small transition probability of going from a non-forest class to a forest class.

5. CONCLUSION

We have proposed a HMM-based multisensor time-series analysis for forest change detection. The change-detection relies on the maximum likelihood criterion that jointly estimate the whole sequence of states. The HMM is regularized by the state transition probabilities, and for our case the method appeared to be robust against phenological/seasonal changes of the vegetation.

In order for this method to be applied to large-scale monitoring, there are many issues that need to be addressed. A critial issues is that the spatial cover of the Radarsat-2 qual-pol is only 25×25 km, and hence, too low to be suitable.

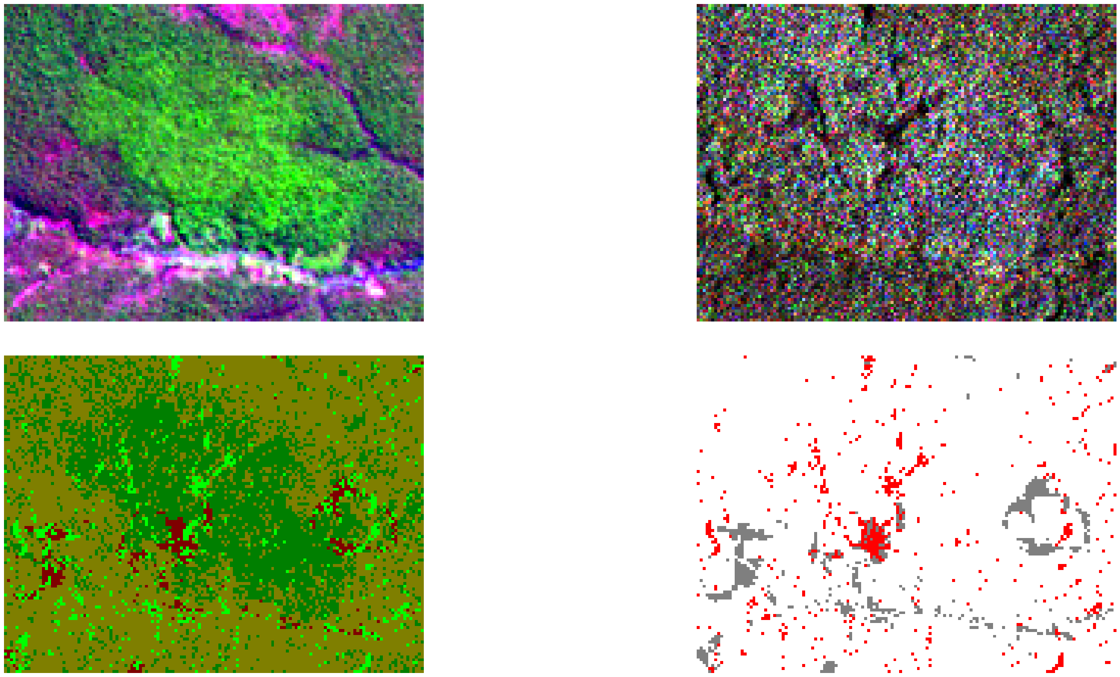

Fig. 2: Upper left: Landsat 5 TM image (1993-07-01). Upper right: Radarsat-2 quad-pol Pauli-decomposition values (2010-03-19). Lower left: Land cover map (2010-03-19) with classes forest (dark green), sparse forest (light brown), grass (light green) and soil (dark brown).Lower left: Change detection image (between 1986-05-15 and 2010-03-19). Red are areas with reduced forest cover, white are forested areas, grey are non-forested areas, and black are non-classified areas.

Dual-pol (e.g. VH/VV) Sentinel-1 data would therefore be interesting for large-scale monitoring.

Further improvements of the method may be obtained by improving the terrain correction of the intensity values in the SAR image, to include all elements of the covariance or coherency matrix of the quad-pol data, and to consider a multi-look texture component [7].

6. REFERENCES

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