SEQUENTIAL CLASSIFICATION OF MODIS TIME SERIES

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ABSTRACT

In this paper a sequential time-varying maximum likelihood classifier is applied on coarse resolution MODIS surface reflectance data. It is shown that good class separability can be obtained after considering only one year of data. Finally it is shown that after NDVI, band 2 has the highest separability of all the MODIS land bands, and band 6 has the lowest separability for the presented case study.

***Index Terms*—** Land cover classification, time-varying maximum likelihood classifier, time series, MODIS, sequential.

1. INTRODUCTION

Land cover classification using remotely sensed data is a critical first step in large-scale environmental monitoring, resource management and regional planning. The classification task is made difficult by severe atmospheric scattering and absorption, seasonal variation, spatial dependence, complex surface dynamics and geometries, and large intra-class variability. Most of the recent research effort in land cover classification has gone into the development of increasingly robust and accurate (and also increasingly complex) classifiers by constructing–often in an ad hoc manner–multispectral, multitemporal, multisource classifiers using modern machine learning techniques such as artificial neural networks, fuzzy-sets, and expert systems. However, the focus has always been (almost exclusively) on increasing the classification accuracy of newly developed classifiers [1, 2]. We would of course like to perform land cover classification (i) as accurately as possible, but also (ii) as quickly as possible. Unfortunately there exists a trade of between these two requirements, since the faster we must make a decision, the lower we expect our classification accuracy to be, and conversely, a higher classification accuracy typically requires that we observe more samples (i.e., we must wait longer for a decision). Sequential classification (no window) provides an attractive solution to handling this trade of between the classification accuracy and the detection delay. It is the objective of this paper to apply sequential classification to coarse resolution Moderate Resolution Imaging Spectroradiometer (MODIS) time series in order to investigate this trade of. Furthermore, this paper deals exclusively with the binary classification task of discriminating between settlements and vegetation land cover types in the Gauteng province of South Africa.

There is a common perception that statistical approaches to land cover classification (such as the maximum likelihood classifier) are not particularly useful, or are too limited for practical purposes. For example, the following excerpt is from the recent book by Tso and Mather [3, p. 61], and several other authors share this view:

> "*As the performance of the statistical maximum likelihood classifier is generally limited by frequency distribution assumptions, in recent years, more elegant classifiers such as artificial neural networks, support vector machines, fuzzy theory-based methods, and decision trees have also been introduced into the field of remote sensing imagery classification. These state-of-the-art classifiers should draw our attention, because they normally are distribution-free, and are able to show a significant level of improvements over traditional methods introduced previously…*"

In some sense this is true, since it is often difficult or impossible to construct reliable statistical models, especially when multiple sources of information have to be taken into consideration.

The claim that maximum likelihood classifiers cannot compete with state-of-the-art multi-source classifiers is however somewhat short-sighted, since a good maximum likelihood classifier can simply become an *additional source* in an *even-more-state-of-the-art* classifier.

Furthermore, statistical models are often more insightful than the black-box approaches of many state-of-the art classifiers. Therefore research into maximum likelihood classification remains important and easily justifiable.

2. CLASSES, STUDY AREA AND DATA DESCRIPTION

2.1. Study Area

The ground truth time series data is extracted from the 8 day composite MODIS MCD43A4 BRDF (Bidirectional Reflectance Distribution Function) corrected 500 m land surface reflectance product corresponding to a total area of approximately 230 km^2 of the Gauteng province of South Africa.[1] The temporal acquisition rate of MODIS MCD43A4 roughly translates to 45 observations per year. The study area is illustrated in Fig. 1 [4].

2.2. Classes

The most prevailing form of land cover change in South Africa is settlement expansion. Two classes of land cover type are thus considered: *natural vegetation* and *settlements*, denoted by v and s. The focus of this paper will be on the classification of settlement and vegetation pixels, since settlement expansion is a relevant problem in South Africa. In this study the settlements class contains pixels consisting of about 50% buildings, and 50% vegetation, whereas the vegetation class contains pixels with more than 90% vegetation.

2.3. Ground Truth Data Set

The ground truth dataset denoted by R, consists of 925 MODIS pixels and was picked by means of (human) visual interpretation of two high resolution Système Probatoire d'Observation de la Terre (SPOT) images from the year 2000 and 2008 respectively. We selected MODIS pixels that according to the SPOT images did not change and had the appropriate percentage land cover type in a MODIS pixel at SPOT resolution. Each MODIS pixel contains eight time series (seven MODIS land bands, and Normalized Difference Vegetation Index) with $I = 368$ observations (extracted between 2000 and 2008). The NDVI time series was computed using the first two spectral land bands. The dataset R is divided into the two classes: settlements (333 pixels) and natural vegetation (592 pixels).

The eight time series extracted from a single pixel is shown in Fig. 2.

3. METHODOLOGY

Assuming we have an observed MODIS pixel $\mathcal{Z}^c = \{\mathbf{z}_k^c\}_{k=\{1,2,\cdots\}}$ which belongs to class $c \in \mathcal{C}$. With

[1]The MODIS MCD43A4 product can be downloaded from http://modis.gsfc.nasa.gov/data/.

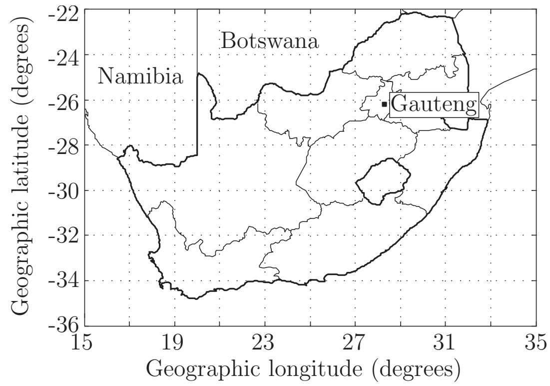


Fig. 1: Time series data representation for a single pixel.

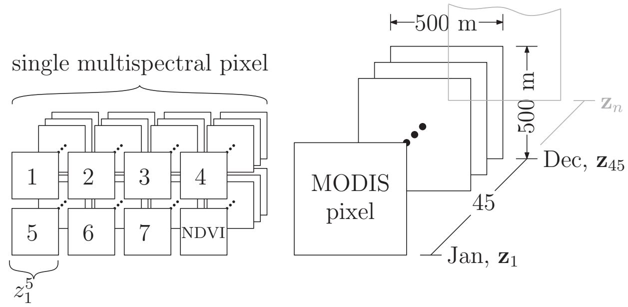


Fig. 2: Time series data representation for a single pixel.

$\mathbf{z}_k^c$ defined as $\{z_k^{c,b}\}_{b\in\{1\cdots7,\text{NDVI}\}}$, where b represents the MODIS band (seven land bands or NDVI). The c superscript is dropped if the class is unknown. We can also look at each band separately $\mathcal{Z}^{c,b} = \{z_k^{c,b}\}_{k=\{1,2,\cdots\}}$.

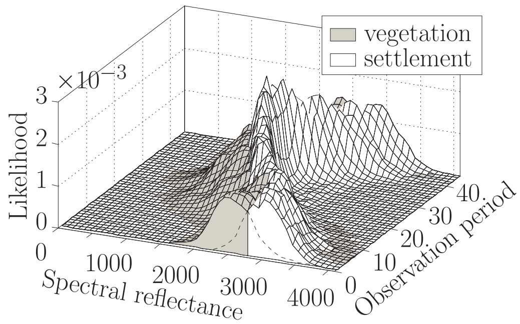
Each observed signal in MODIS band b belonging to the same class $c \in \mathcal{C}$ is a sample path of a stochastic process $\{Z_k^{c,b}\}_{k=\{1,2,\cdots\}}$. Since $\{Z_k^{c,b}\}_{k=\{1,2,\cdots\}}$ is a stochastic process we can determine its first order statistical description.

The first order statistical description is equivalent to the set of probability density functions at each time step k, represented with $\{q_k^{c,b}\}_{k=\{1,2\cdots\}}$. If we assume that the MODIS data contain no inter annual variation, in other word we assume that MODIS time series is periodic (45 observations in a year), then we have that $q_k^{c,b} = q_{k+45}^{c,b}$. To estimate $q_i^{c,b}$ at time of the year i we first group all the observations of a particular time of the year together with

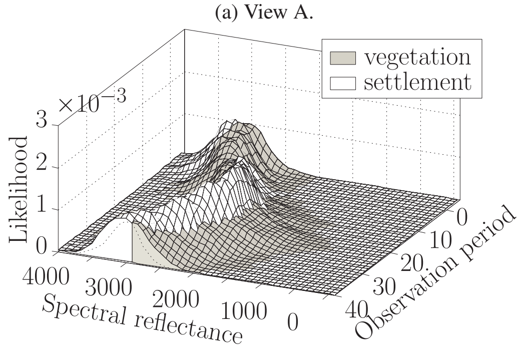
$$\mathcal{G}_i^{c,b} = \underset{i+45n}{\text{pr}}\ \mathcal{Z}^{c,b},\ n = 0, 1, \cdots, N,\ 1 \le i \le 45, \quad (1)$$

where pr is the projection operator and N is the number of years. We can determine $\mathcal{G}_i^{c,b}$ for each observed pixel in class c. After unifying all the computed $\mathcal{G}_i^{c,b}$ we can estimate $q_i^{c,b}$ using kernel density estimation.

Now assume we have an observed MODIS pixel $\mathcal{Z}$ with time series $\{z_k^b\}_{k=\{1,2,\cdots\}}$ in each spectral band of which the class is unknown. We can now consider the task of deciding between two simple statistical hypotheses, $\mathcal{H}_0$ (settlement)



(a) View A.



(b) View B.

Fig. 3: Time-varying probability density function ambiguity for MODIS band 2.

and $\mathcal{H}_1$ (vegetation), using information from only a single spectral band.

$$\mathcal{H}_0 \quad : z_k^b \sim Q_k^{c_0,b}, \quad k = 1, 2, \ldots$$

versus

$$\mathcal{H}_1 \quad : z_k^b \sim Q_k^{c_1,b}, \quad k = 1, 2, \ldots$$

where for each observation period k, $Q_k^{c_0,b}$ and $Q_k^{c_1,b}$ are two probability distributions with associated probability densities $q_k^{c_0,b}$ and $q_k^{c_1,b}$, respectively. The variables c_0 and c_1 refer to the settlement and vegetation class respectively. Further assume that hypothesis $\mathcal{H}_1$ occurs with prior probability π, and $\mathcal{H}_0$ with prior probability $1 - \pi$.

We use the sequence of observations $\{z_k^b\}_{k=\{1,2,\cdots,\}}$ and define the posterior sequence in the following manner [5]:

$$\pi_n^\pi = \frac{\pi_{n-1}^\pi q_n^{c_1,b}(z_n^b)}{\pi_{n-1}^\pi q_n^{c_1,b}(z_n^b) + (1 - \pi_{n-1}^\pi) q_n^{c_0,b}(z_n^b)}, \quad n = 1, 2, \ldots, \tag{2}$$

where $\pi_0^\pi = \pi$.

The maximum likelihood solution of the time-varying classification task is then given by

$$\delta_n = \begin{cases} 0 \ \text{(i.e. settlement)}, & \text{if } \pi_n^\pi \leq 0.5 \\ 1 \ \text{(i.e. vegetation)}, & \text{if } \pi_n^\pi > 0.5, \end{cases} \tag{3}$$

if we make a decision at observation n.

One immediately apparent advantage of the time-varying model considered here is that the time-varying model compensates for seasonal behavior. During the times of the year when the two classes are less separable, the posterior sequence grows slower in confidence than during other parts of the year. Fig. 3 shows the time-varying behavior of the settlement and vegetation classes for band 2, from which it is clear that some periods of the year (such as spring and early summer) are more separable than others.

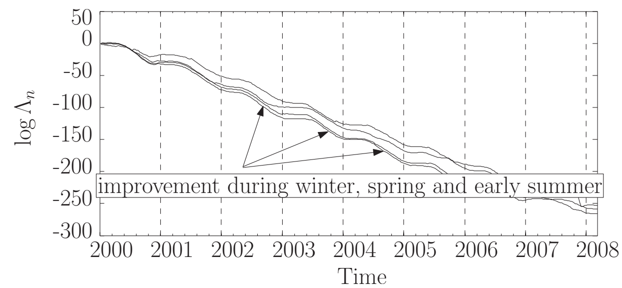


Fig. 4: The LLR over time in spectral band 4. The LLR is defined as $\sum \ln \frac{q_n^{c_1,b}(z_n^b)}{q_n^{c_0,b}(z_n^b)}$ and is an alternative approach to the posterior sequence π_n^π. The details can be found in [1].

In fact, different bands have different periods during which they are easily separable. Fig. 4 shows the Log-likelihood Ratio (LLR) as a function of time for several vegetation pixels in spectral band 4, in which a sharp decline in the LLR indicates that the classes are easily separable, and a plateau indicates that the classes are difficult to separate. From Fig. 5 we notice that the spectral separability profile of band 4 and band 2 are different from each other.

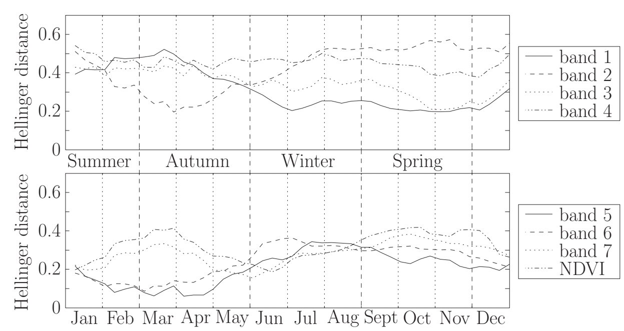


Fig. 5: Hellinger distances indicating class separability over time.

We can also evaluate the class separability based purely on the pdfs (probability density functions). The Bhattacharya coefficient is commonly used as an indicator of class separability, and is given as

$$BC(p, q) = \int_{-\infty}^{\infty} \sqrt{p(x)q(x)}\, dx, \tag{4}$$

where p and q denote two probability density functions (not necessarily distinct).

However, the Bhattacharya coefficient does not satisfy the triangle inequality, so we choose to consider the related Hellinger distance instead (which *does* satisfy the triangle inequality). The Hellinger distance $(0 \leq HD \leq 1)$ between two (continuous or discrete) probability density functions can be expressed in terms of the Bhattacharya coefficient

$$\begin{aligned} HD(p,q) &= \sqrt{1 - BC(p,q)} \\ &= \left[1 - \int_{-\infty}^{\infty} \sqrt{p(x)q(x)}\, dx\right]^{1/2}, \end{aligned} \quad (5)$$

where p and q denote two probability density functions. A Hellinger distance of $HD \approx 0$ indicates that the classes are not separable, whereas a distance $HD \approx 1$ indicates that the classes are trivially separable. Fig. 5 gives the Hellinger distances between the residential and vegetation classes for the entire year. Overall the results correspond well to those presented in Fig. 4.

4. RESULTS

The single band classification results are shown for the temporal time-varying maximum likelihood classification approach in Table 1, where FP refers to the false positive rate and FN refers to the false negative rate. Table 1 indicates that band 2 performs the best.

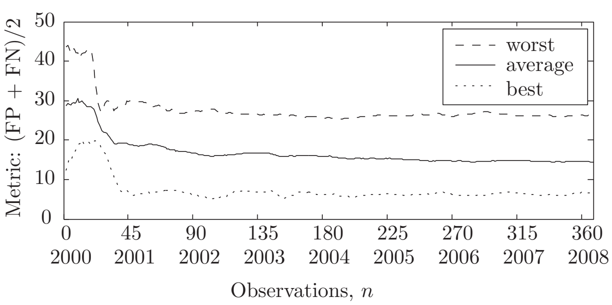


Fig. 6: Maximum likelihood classification metric, (FP + FN)/2, over all the single band classifiers (including NDVI) as a function of the number of observations, n.

It is also worthwhile to consider the time-varying maximum likelihood classification task as a function of the number of observations n, which is shown in Fig. 6.

With reference to Fig. 6 we can see that there is very little gain (in terms of classification accuracy) after the first year has elapsed. This result seems plausible, since the spectral responses of both residential and vegetation surfaces are expected to be roughly the same from one year to the next. Fig. 6 seems to suggest that a good sequential classification strategy is to classify within the first year of observation.

Table 1: Classification metrics, defined as (FP+FN)/2, for time-varying maximum likelihood classification with $n = 368$ observations.

Band	(FP+FN)/2
Band#1	16.0
Band#2	6.9
Band#3	15.0
Band#4	12.2
Band#5	18.8
Band#6	26.4
Band#7	14.0
NDVI	6.5

5. CONCLUSION

The time-varying maximum likelihood classification of MODIS time series revealed that effective classification can be done by using only the observations of the first year. It should now be clear that if we use less observations the performance of our classifiers becomes weaker.

6. REFERENCES

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