Alignment of Growth Seasons from Satellite Data

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***Abstract*— This work concerns the alignment of growth seasons based on satellite data. This work is motivated by a high mountain vegetation classification problem in Norway. Vegetation classes are characterized by their temporal evolution through a growth season. Data of high spatial resolution, like LANDSAT data, are often temporally sparse. In order to get a longer sequence of images, data from different years can be combined into one single synthetic sequence.**

We describe a method for determining the correspondence between the chronological time of the image acquisition and the time at which the phenological state of the vegetation cover shown in the image would typically occur.

The task is considered as a minimization problem and is solved by dynamic programming. The methodology is based on the normalized difference vegetation index (NDVI) computed from data having a coarse spatial resolution such as MODIS or AVHRR data.

The proposed methodology has been tested on data from several years covering a region in Norway including mountainous areas. It is evident from plots of the original data that NDVI curves from different seasons are shifted relative to one another. By applying the proposed time warping methodology to adjust the time scale within each year the shifts become less apparent. We conclude that the methodology can be used for alignment of growth seasons from satellite data.

I. Introduction

Vegetation mapping using satellite images is an active research area. Classification of high mountain vegetation in Norway can be based on LANDSAT data (see [1]) or other kinds of data of high spatial resolution. Often the classes are characterized by the temporal evolution through a year. Due to the weather conditions in Norway the LANDSAT data are however temporally very sparse. Typically, one can expect only two to three acceptable LANDSAT images per summer season (May - September). It is therefore expected that classification performance will be improved by adding more images so that information from a larger part of the growth season can be used. In order to get a longer sequence of images, data from different years need to be combined into one single synthetic sequence. The work described here is concerned with the task of determining the point in time within the phenological season that each image represents. Completing this task successfully is crucial to the classification of a seasonally varying vegetation cover. The task is nontrivial since the temporal evolution through the growth season varies from year to year.

MODIS and AVHRR data are unsuitable for classification of high mountain vegetation in Norwegian areas due to their coarse spatial resolution and the small vegetation patches. However, MODIS and AVHRR provide a more frequent coverage than LANDSAT. Consequently, MODIS or AVHRR data from a given growth season contains more information about the temporal evolution through the given year. Therefore, we want to perform a temporal alignment of LANDSAT data based on MODIS or AVHRR data.

The normalized difference vegetation index (NDVI) is well related to the proportion of absorbed photosynthetically active radiation, a key variable of the biomass production process (see [2]). Thus, NDVI can be used for the purpose of studying the phenological evolution through a growth season. We model the observed NDVI through a given growth season statistically. The model includes a description of the noise, and a time warping function mapping the actual season to the standardized season. Further details concerning the model are described in Section II.

Finding the appropriate time warping function is the main task in this study. The time warping is found by solving a minimization problem. This is described in Section III. The idea of time warping is not new. It has been successfully applied to many areas such as speech recognition [3]. However, to our knowledge it has not previously been applied to alignment of growth seasons based on satellite data.

In Section IV, we show how the time warping works on data from several years covering a region in Norway including mountain areas. The results show that the methodology is suitable for alignment of growth seasons from satellite data.

II. Model

We want to model the phenological evolution through a growth season. Obviously, different seasons have different evolutions. The evolution is described by a mapping w_y from chronological time to phenological time. The subscript y (= year) indicates that the mappings from two different years are different. In an average season w_y should be close to the identity, that is $w_y(t) = t$ where t is the time variable (day). If the spring comes early $w_y(t) > t$ during the spring. Similarly, if the spring comes late $w_y(t) < t$ during the spring.

We do not observe w_y directly. MODIS or AVHRR data, however, contains information about the w_y. From satellite data we can compute the normalized difference vegetation index (NDVI) given by

$$NDVI = \frac{\rho_{nir} - \rho_{vis}}{\rho_{nir} + \rho_{vis}}, \tag{1}$$

where ρ_{nir} and ρ_{vis} are the reflectances in the visible and the near-infrared bands. NDVI should be computed after preprocessing, including geometric and radiometric correction. Pixels occluded by clouds should be removed.

Assume that we have data from $t_1, t_2, \ldots, t_n$. At time t_i we can extract the maximum NDVI X_i from our region of interest. We have chosen to extract the maximum NDVI because this value is not too sensitive to cloud coverage and pixels from non-vegetation areas. The mean NDVI is more sensitive to these factors.

We want to recover w_y from the observations $X_1, X_2, \ldots, X_n$. If sampled continuously, without noise, the observed NDVI would normally be an increasing function in time through the first part of the season (spring and early summer) and decreasing though the second part (late summer and fall). In this work, a double logistic function is used for modeling the ideal NDVI profile of a standardized season. Previous research shows that this is a reasonable approximation (see [4]), at least for homogeneous canopies consisting of individual crops. In practice, the observations are corrupted with noise, and there are temporal gaps in the observed sequence. Variation in growth speed causes additional deviation from the ideal profile. Therefore, the observed NDVI through a given growth season is modeled statistically.

The observations are modeled as

$$X_i = g(w_y(t_i)) + \epsilon_i, \tag{2}$$

where the ϵ_is are independent with zero expectation and $g(t)$ is the NDVI value at t in a standardized season. We expect that the magnitude of ϵ_i is small compared to the range of g.

The function g is a double logistic function and is given by

$$g(t) = g_{-\infty} + \frac{h}{1+\exp(-r_u(t-t_u))} - \frac{h+g_{-\infty}-g_{\infty}}{1+\exp(-r_v(t-t_v))}, \tag{3}$$

Here $g_{-\infty}$ and g_{∞} are the limits as the time t goes to $-\infty$ and ∞, respectively. The parameters r_u and r_v are approximate slopes at the two inflection points where the graph is steepest. The inflection points occur approximately at t_u and t_v. The parameter h is related to the range of g. If the region of interest is covered by snow during the winter we can set $g_{-\infty} = g_{\infty} = 0$. The other parameters can be estimated using the method of least squares.

It is reasonable to put some restrictions on the mapping w_y. We assume that the following conditions are satisfied:

1) $w_y(t_b) = t_b$ and $w_y(t_e) = t_e$, where t_b and t_e are the beginning and the end of the growth season, respectively.
2) w_y is strictly increasing.

We expect that $w_y(t)$ is not very different from t. In addition, we expect that the derivative of w_y is close to 1. Moreover, w_y should be fairly smooth. It is unlikely that the derivative of w_y is very large or very small.

III. Algorithm

A simple approach to the task of finding an appropriate mapping from chronological time to phenological time is to consider the task as an minimization problem. We want to determine the mapping w on m equally spaced time points $t_b+\Delta t, t_b+2\Delta t, \ldots, t_b+m\Delta t$ where t_b is the beginning of the growth season. The spacing Δt is chosen such that $t_b+(m+1)\Delta t = t_e$ where t_e is the end of the growth season.

In Section II we described the desired properties of the time warping function w. Based on these properties we define an object function E by

$$E(w) = E_o(w) + \alpha(E_c(w) + E_d(w)) + \beta\, E_p(w) \tag{4}$$

where

$$E_o(w) = \sum_{i=1}^{n} (X_i - g(w(t_i)))^2, \tag{5}$$

$$E_c(w) = \sum_{j=0}^{m} \left(\frac{w(t_b+(j+1)\Delta t) - w(t_b+j\Delta t)}{\Delta t} - 1\right)^2, \tag{6}$$

$$E_d(w) = \sum_{j=0}^{m} \left(\frac{\Delta t}{w(t_b+(j+1)\Delta t) - w(t_b+j\Delta t)} - 1\right)^2, \tag{7}$$

$$E_p(w) = \sum_{j=1}^{m} (w(t_b+j\Delta t) - (t_b+j\Delta t))^2, \tag{8}$$

and α and β are constants to be tuned.

If $E_o(w)$ is small, the warped data are close to the ideal NDVI profile of a standardized season. If $E_c(w)$ and $E_d(w)$ are close to zero, the derivative of the time warping function is close to one. Keeping $E_c(w)$ small prevents the derivative of w from being large. Similarly, if $E_d(w)$ is fairly small, the derivative of w cannot be close to zero. If $E_p(w)$ is small, $w(t)$ will not be very different from t.

We assume that

$$w(t_b + j\Delta t) = t_b + k_j \Delta s \tag{9}$$

for some integer k_j. The constant Δs is the resolution of the range of w. This makes the class of functions w finite. However, the class could be very large. We assume that w is strictly increasing and $w(t_b) = t_b$ and $w(t_e) = t_e$.

We want to determine the function w_y that minimizes $E(w)$. The minimizing function w_y can easily be determined by dynamic programming [3].

IV. Results and discussion

To test the proposed approach for aligning growth seasons we applied it to a a sequence of NDVI composites extracted from NOAA AVHRR data from the period 1982-2003. This data set consists of 24 images, evenly spaced in time, from each year. We also run the algorithm for NDVI computed from MODIS data from 2003 and 2004. The MODIS data set used in this work consists of 91 and 65 images from 2003 and 2004, respectively. The data come from a region called Fron in Norway containing high mountain vegetation. For each year we determined a time warping function w_y by minimizing

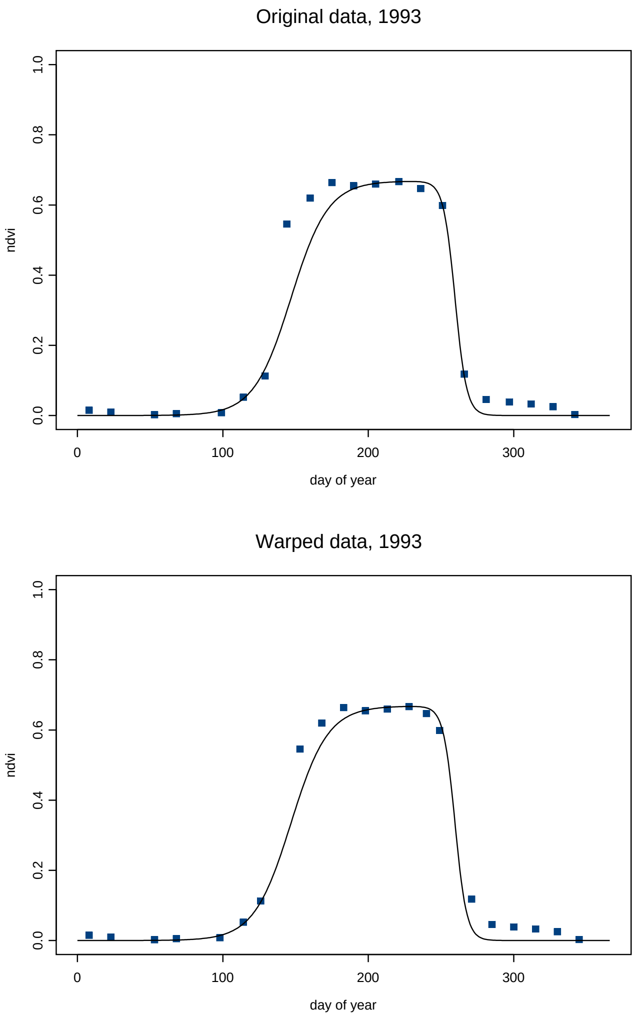

Fig. 1. Original NDVI data and warped results for 1993 along with the curve representing the expected NDVI evolution.

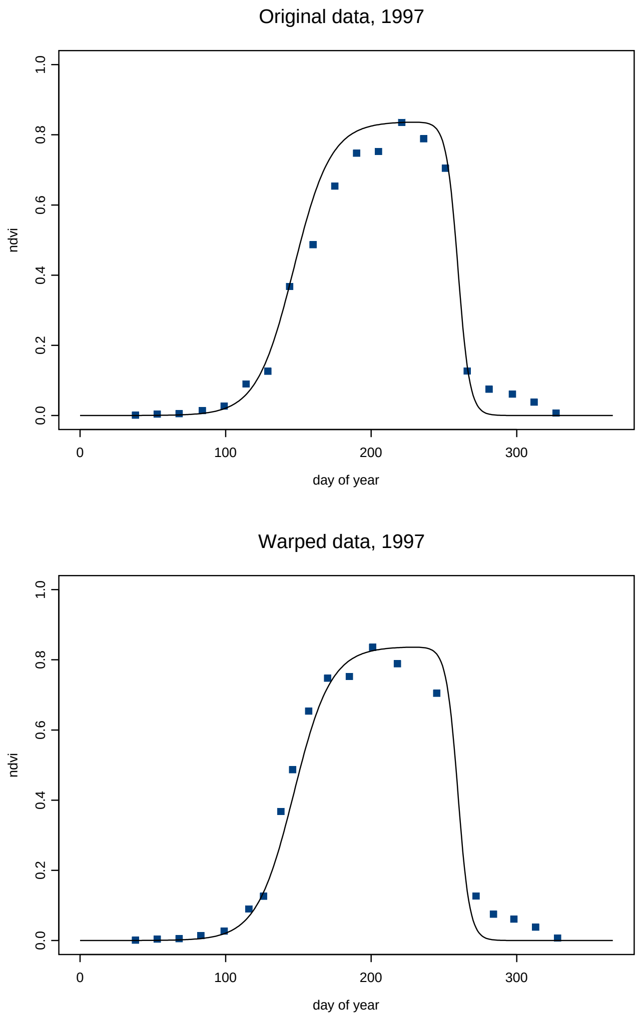

Fig. 2. Original NDVI data and warped results for 1997 along with the curve representing the expected NDVI evolution.

$E(w)$ in (4). We used the same reference function g for all years except that the parameter h in (3) was adjusted such that the maximum of g became equal to the maximum of the observed NDVI for the given year. In future studies, the impact of varying the various parameters involved should be investigated.

We show the results for two of the years, 1993 and 1997, in Figure 1 and Figure 2. From the original data we see that the spring comes early in 1993 and late in 1997. We see that the warped data are closer to the reference function than the original data. However, for 1993 the difference between the original data and the warped data is rather small.

Figure 3 and Figure 4 show two LANDSAT images from Fron. The first one is from May 23rd 2004 while the second is from June 5th 1997. Despite the fact that the first image appears earlier in the chronological year than the second, it is apparent that the first one shows a later phenological state. The first image contains more green pixels and less snow pixels than the second. This is due to the fact that the spring came earlier in 2004 than in 1997. By applying our methodology we can map the dates from the two years into the dates of the standard season. This results in an interchange of the order of the two images, which is what we wanted. The methodology can therefore be applied to ordering images from different years with respect to the phenological states shown in the images. Thus, we have proposed a useful tool for combining data from several years into one single synthetic sequence.

V. Conclusion

We have proposed a methodology for alignment of growth seasons from satellite data. The proposed methodology has been tested on data from several years covering a region in

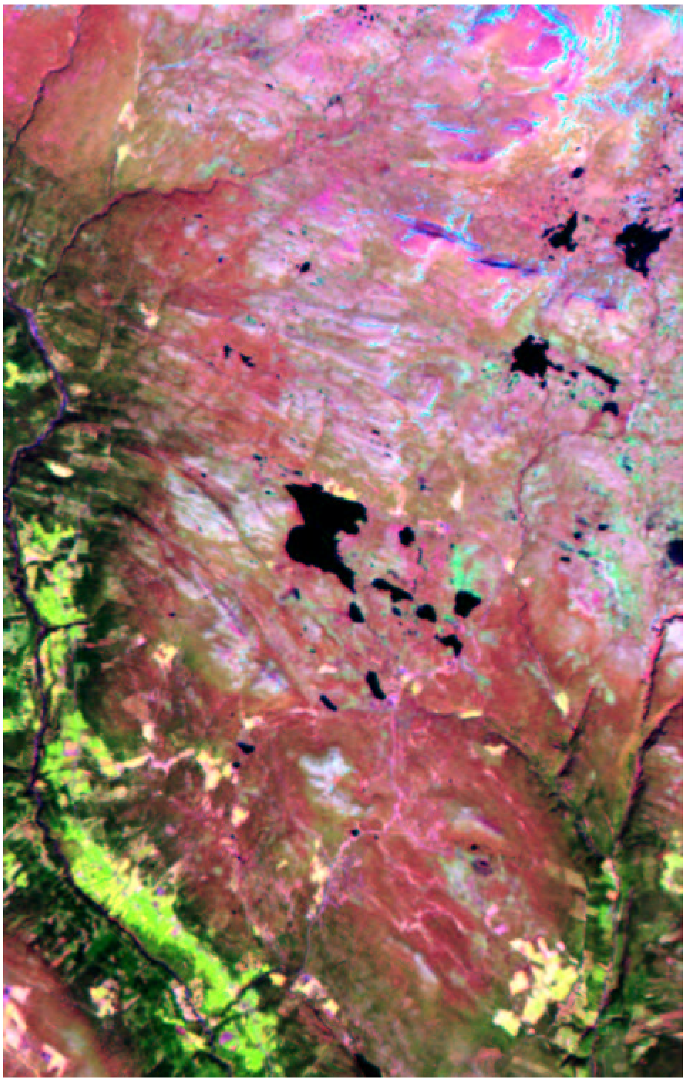

Fig. 3. LANDSAT data from May 23rd 2004. The image shows the region called Fron.

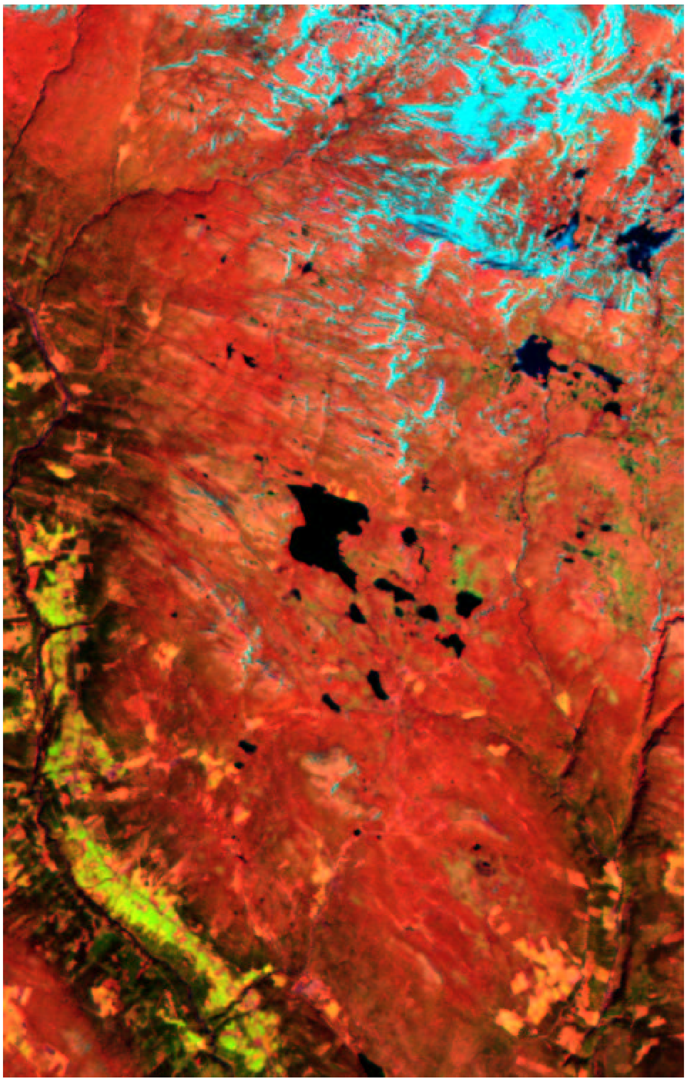

Fig. 4. LANDSAT data from June 5th 1997. The image shows the same region as Figure 3.

Norway including mountain areas. The results show that it is possible to combine data from several years into a sequence of observations from one season. We expect that the methodology will serve as a useful tool in multi-temporal classification.

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