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Separabilities of Forest Types in Amplitude-phase Space of multi-temporal MODIS NDVI

Thomaz Chaves de A. Oliveira [1,]
Luciano Teixeira de Oliveira [1]
Luis Marcelo Tavares de Carvalho [1]
Adriana Zanella Martinhago [1]
Fausto W. Acerbi Júnior[1]
Ludimila Portela Zambaldi Lima[1]

[1] Departamento de Engenharia Florestal - Universidade Federal de Lavras - UFLA
Caixa Postal 3037 – 37.200-000 - Lavras - MG, Brasil
thomazchaves@gmail.com

Abstract. This paper describes a methodology to map forests based on vegetation phenology. It relies on amplitude/phase vector-space information of multi-temporal MODIS NDVI. This information is provided by applying the HANTS algorithm Verhoef (1996) which performs Fourier analysis on the temporal NDVI images. The algorithm was conceived specifically for the removal of cloud contaminated and low quality pixels on the data set. For the purpose of this work, the output FFT (complex number images) images which were converted into amplitude-phase information to each pixel were analyzed for vegetation differentiation purposes. A vegetation classification was performed in the amplitude-phase data set as input to a neural network. Statistics from the resulting classification showed that information on the amplitude-phase space of harmonic analysis do not improve the classification, and perform worse than the original data set.

Keywords: remote sensing, image processing, time series, NDVI, MODIS, amplitude-phase, vegetation indices.

1. Introduction

The human action over the years and its consequences over the environment led to concerns over the Earth’s future, environment and climate. Recently some environmental problems such as global warming and deforestation have lead to the necessity of monitoring land cover and to detect changes in global and local scale.

One forest type which is in constant threat by human activity is the deciduous forests of Minas Gerais state, Brazil. These deciduous forests are phytophysiognomies that are characterized by an alternating cycle of dry and wet seasons. The period of dryness occurs from the middle of April until September. The wet season starts in October and goes up to the Month of March. This leads to an intensified variation of greenness in vegetation and landscape characterization throughout time. The variation of greenness of the semi-deciduous forests is not as intense, due to their occurrence in regions of intensified humidity, near rivers for an example. Oliveira (2004). These differences can be witnessed in Figure 1.

Mapping soil occupation and use through means of remote sensing data has been a research of growing interest throughout past decades and its complexity, peculiarities and state of art of computational aids differentiate by far the past conventional means of cartography. Advances in computer science have aided the proper extraction of relevant information from remotely sensed images as well as the effective use of geographical information systems to store, analyze and present all sorts of georeferenced information Carvalho (2001).

Since some objects on the Earth´s surface reflect the electro-magnetic energy in the same way when sensed with a multi-spectral scanner, in addition ‘objects’ reflectance may vary according to growth stage, phenology, humidity, atmospheric transparency, illumination conditions, etc. These drawbacks led to alternative features to enable the discrimination of land cover classes with similar reflectance behavior Carvalho et al. (2004).

(a) (b)

Figure 1 – (a) Deciduous forest, (b) semi-deciduous forest - Source Oliveira (2004)

This phenomenon occurs when mapping the deciduous forests in our region of interest, due to geographical variation and the high range of vegetation dynamics, the deciduous forests of Minas Gerais tend to lead to incorrect classification through the means of automated computer aided mapping through feature extraction. Research however, suggests that remotely sensed time series data could possibly resolve these misclassification errors and lead to an accurate mapping of this phytophysiognomy Oliveira (2004).

Timing is very important when attempting to identify different vegetation types or to extract useful vegetation biophysical information (e.g. biomass, chlorophyll, characteristics) from remote sensed data Jensen (2000). Multi-temporal satellite images composites are now of standard use in land cover classification of large areas at regional and global scales Carrão et al. (2007).

This works objective is to find whether amplitude-phase images originated from Fourier analisys can be used as input data sets to provide accurate mapping to the occurrences of decidual forests. Theses amplitude-phase vector-spaces retain temporal phenology information and are originated from the MODIS sensor aboard the Aqua and Terra platforms.

2. Methods

2.1 The MODIS Sensor

MODIS data products offer a great opportunity for phenology-based land-cover and land-use change studies by combining characteristics of both AVHRR and Landsat, including: moderate resolution, frequent observations, enhanced spectral resolution, and improved atmospheric calibration Galford et al. (2007).

The AVHRR sensor was originally designed for meteorological applications, and has only two spectral bands (red and near-infrared) that can be used to generate the spectral indices of vegetation in vigor. The new generation MODIS sensor has a number of advantages over AVHRR, including more spectral bands that can be used for vegetation analysis Yu et al. (2004).

2.1.Remote Sensing Vegetation Dynamics

Field-based ecological studies have demonstrated that vegetation phenology tends to follow relatively well defined temporal patterns. For example, in deciduous vegetation and many crops, leaf emergence tends to be followed by a period of rapid growth, followed by a relatively stable period of maximum leaf area Zhang et al. (2003). Different types of vegetation have different temporal growth patterns (i.e., different growth and senescence rates) Bruce et al. (2006).

2.1.3 MODIS Vegetation Indices

MODIS VI products are appropriate for vegetation dynamics studies and characterization. MODIS-VI are found to be sensitive to multi-temporal (seasonal) vegetation variations and to be correlated with LAI across a range of canopy structure types species and lifeforms, land cover variations. The MODIS NVDI and EVI VI demonstrate a good range and sensitivity for monitoring and assessing spatial and temporal variations in vegetation amount and condition. The seasonal profiles outperform in sensitivity and fidelity the equivalent AVHRR-NDVI profiles particularly in atmosphere with water vapor contents. Huete et al. (2002).

A vegetation Index should maximize sensitivity to plant biophysical parameters; normalize or model external such as sun angle, viewing angle, and the atmosphere for consistent spatial and temporal comparisons; normalize internal effects such as canopy background variations; a vegetation index may preferably coupled with a measurable biophysical parameter such as biomes, LAI, or APAR Jensen et al. (2002). MODIS Vegetation Index products correlate and respond positively to increases in PAI and LAI across a range of canopy structure types and species life forms Huete et al. (2002).

2.2 Study Site

Due to the widespread occurrence of deciduous forests in the state of Minas Gerais and due to the state's large extent, 586.528 km², this study was conducted in a smaller area of interest, near the towns of Matias Cardoso and Manga, that has following coordinates: (14º40'37,06" S , 44º02'41,28"W),(14º51'59,33"S, 43º47'13,16"W). The Datum that was used was WGS-84, and the projection was Albers Equal Area. This area was primarily chosen because of acknowledged occurrence of deciduous forest. The area was also chosen so that the chosen methodology could be spreaded to other areas in future work. The NDVI time series was derived from the MOD13 product, which has a spatial resolution of 250m, and has a 16-day compositing period. The original data, downloaded from the MODIS FTP was reprojected using MRT(MODIS Reproduction Tool) A set of temporal images from the Landsat TM sensor were also used as auxiliary data. These images were collected from summer and winter dates to each area and were used so the exact locations of the deciduous forests and other types of vegetation were know previously and methodology validation. The original data set was resampled to 12 values to each year. The database included the years of 2003, 2004 and 2005.

Due to the presence of factors apart from land surface characteristics, several factors such as: cloud contamination, atmospheric variability, and bi-directional reflectance, these factors affect the stability of the satellite derived NDVI. Thus compositing methods have been developed to eliminate these effects. The compositing Method for the AVHRR NDVI data source is the MVC (Maximum value composite), which selects the maximum NDVI value on a per pixel basis over a set of compositing period Wang et al. (2004).

The MODIS compositing method operates on a per-pixel basis and relies on multiple observations over a 16-day period to generate a composite VI. Due to sensor orbit overlap and multiple observations, a maximum of 64 observations may be collected in a 16 compositing period. Once all the 16 days of observation are collected, the MODIS VI algorithm applies a filter to the data based on quality, cloud, and viewing geometry. Only the higher quality cloud free, filtered data are retained for compositing Huete et al. (2002).

At regional and larger scales, variations in community composition, micro and regional climate regional, climate regimes, soils, and land management result in complex spatio-temporal variation in phenology. Further, some vegetation types exhibit multiple modes of growth and senescence within a single annual cycle. Therefore remote sensing methods need to be sufficiently flexible to allow for this type of variability Zhang et al. (2003).

2.3 Fourier Analysis

The Fourier Analyses or Harmonic analyses have been used traditionally to solve some differential equations and also some partial equations in Math and Physics. Its main objective is to approximate a function in time domain by a function, which contains a linear combination of harmonics (sinusoids) Morettin (2006). The most basic property of the sinusoids that makes them suitable for the analysis of time series is their simple behavior under a change in time scale Bloomfield (1976).

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-2j\pi ft}dt \qquad (1)$$

$$x(t) = \int_{-\infty}^{\infty} X(f)e^{2j\pi ft}dt \qquad (2)$$

Figure 2 (1)Fourier transform to the frequency domain, (2) Inverse Fourier transform

Fourier analysis (Figure 2) have traditionally used for denoising and curve fitting in MODIS VI data sets Colditz et al. (2007) Bruce et al. (2006) Yu et al. (2004) Wang et al. (2004). If the original data is discrete rather than continuous, the discrete rather than continuous, the discrete Fourier transform (DFT), which requires regular spacing on samples within the temporal domains, should be applied Wang et al. (2004).

There is a drawback in this approach, since the NDVI images are composite images of different dates. The pixels have different acquiring dates that lead unequal time spacing. However, the next generation Hants algorithm Harmonic Analysis of Time Series (HANTS) was developed to deal with time series of irregularly spaced observations and to identify and remove cloud contaminated observations Verhuef (1996) Roerink et al. (2000).

This algorithm considers only the most significant frequencies expected to be present in the time profiles (determined, for instance, from a preceding FFT analysis), and applies a least squares curve fitting procedure based on harmonic components (sines and cosines) Verhoef et al. (1996), Roerink et al. (2000). For each frequency the amplitude and phase of the cosine function is determined during an iterative procedure. Input data points that have a large positive or negative deviation from the current curve are removed by assigning a weight of zero to them. After recalculation of the coefficients on the basis of the remaining points, the procedure is repeated until the maximum error is acceptable or the number of remaining points has become too small Roerink et al. (2000).

Many different phenological indicators have been defined in various satellite-based studies. The advantage of the HANTS algorithm is that the output consists of a completely smoothed NDVI profile which is convenient for calculating derivatives. De Wit. (2005) The calculations of derivates are very important so you can estimate the start of growing season and senescence dates Sakamoto et al. (2005).

The version of HANTS used was implemented in IDL by De Wit (2005) and is under the GNU General Public License.

2.4.Amplitude-phase Vector spaces

Harmonic analysis can be used aiming the reduction the dimensionality of the data. Another advantage is that each pixel is treated individually being independent from the rest of the image. It is also possible to choose the period of analysis relating to the frequency of the studied phenomenon, thus this technique serves well as a filter to noise originated from cloud contamination in the time series and from noise resulting from pre-processing that is not periodic. The magnitude and phase of a waveform can be calculated from the complex number resulting from a FFT. The magnitude corresponds to half of wave's peak value, and the phase corresponds to the shift from the origin to the wave's peak value from 0 to Π (equations 1 and 2) Lacruz (2006). The time series of NDVI data was the input data set in HANTS algorithm. The algorithm then outputs a smoothed time series, and a FFT vector for each pixel. These FFT vector contain the complex conjugate for each harmonic and the mean value of the time series the equations 3 and 4 were used to compute the amplitude and phase of each harmonic.

By computing the amplitude and phase of each harmonic, the dimensionality of the data set had been dramatically reduced from 36 to 7, mean value, amplitude and phase of the first 3 harmonics. Some authors such as Yu (2004) Coldiz et al. (2007) suggest that only the first three harmonics depict biophysical parameters and should be used for further analysis. In this work, this could be observed, only the 1 year and the 6 months harmonic revealed constant patters as the others revealed to be noisy at low values.

$$Cj = \sqrt{Aj^2 + Bj^2} \tag{3}$$

Calculation of the amplitude of a Harmonic from the complex conjugate

$$\phi = \tan^{-1} \frac{B_j}{A_j} \tag{4}$$

Calculation phase angle ϕ

2.5.Differentiating forests by computer aided methods

As commented earlier, the main objective of this work is to create a methodology to differentiate the deciduous forests from other phytophisiognomies based on time series of NDVI data. So for this purpose, we need an algorithm that has the capability for separating this vegetation from the others. For Moreira (2003) an automatic image identification and classification can be understood as the analyses and the manipulation of images through computational techniques, with the goal of extracting information regarding an object of the real world.

2.6 Neural Networks

Humans and other animals process information with *neural networks*. These are formed from *trillions* of neurons (nerve cells) exchanging brief electrical pulses called action potentials. Computer algorithms that mimic these biological structures are formally called artificial neural networks to distinguish them from the squishy things inside of animals. Smith (1998) Even though some researchers do not recognize the neural networks as being the general natural solution surrounding the problems of recognizing patterns on processed signals, it can be noticed that a well trained network is capable of classifying highly complex data. The use of neural networks in pattern recognition and classification has grown in the last years in the field of remote sensing. Kanellopolous (1997). For comparison reasons other two different types of networks were used. An unsupervised neural networks called Self Organizing Maps (SOM) Kohonen (1990), were used to classify the vegetation. Unsupervised learning does not need input samples for pattern recognition. A Fuzzy ArtMap is a clustering algorithm that operates on vectors with fuzzy analog input patterns (real numbers between 0 and 1) and incorporates an incremental learning approach which allows it to learn continuously without forgetting previous learned patterns. For Mather (1999) the use of soft (fuzzy) classification paradigms with neural networks is adequate when we want to avoid errors of classification due to ambiguity of the generated classes. This type of network considered in the present study was based on the ART (Adaptative Resonance Theory), which exhibits a high degree of stability in order to preserve significant past learning, but remain enough adaptable to incorporate new information whenever it might appear.

2.7. Training and Classification and Accuracy Assessment

The classification proceeded, using training samples, so that the algorithm can "learn" to recognize the patterns. The training phase must happen to each algorithm before it can be used for classification. It was used the same training data for both original and denoised time series. The multi layer perceptron had the following characteristics which were obtained by testing: 7 layers on the hidden layer, learning rate of 0.01, momentum factor of 0.5, 20 training samples per category, 10 testing samples per category and liner activation function as well as the sigmoid activation function for comparison purpose. The network was trained with 10000 iterations. It was used the same training data for both original and denoised time series. The SOM does not need training, however was parameterized as following: maximum learning rate of 1.0, minimum learning rate of 0.5, minimum gaining term of 0.0001, max gaining term of 0.0005, LVQ2 fine tuning rule, the algorithm was ran with 1000 epochs. The Fuzzy ARTMAP had the following parameters for ARTa: choice parameter of 0.01, learning rate of 0.5, vigilance parameter of 0.98. The ARTb had learning rate of 0.5 and vigilance parameter of 1.

In order to compare the results of classification, we need to parameterize the classification among different classifiers. In order to accomplish this, a set of accuracy samples was aquired. With the accuracy samples a confusion matrix was generated, by which the Kappa coefficient was extracted from. By doing this, we can compare statistically the performance of each algorithm and for this data set Mather (1999).

3. Results

Results show that the amplitude-phase data set proved to be inefficient to differentiate forests. This can be witnessed in Tables 1, 2, 3 and 4.

Table 1 - multi layer perceptron with linear activation function classification comparison

Multi layer perceptron with linear activation function		
Data set	**Accuracy (%)**	**Kappa Coefficient**
Original time series	**87,5000**	**0,8571**
Amplitude/Phase	47,5000	0,4000

Table 2 - multi layer perceptron with sigmoidal activation function classification comparison

Multi layer perceptron with sigmoidal activation function		
Data set	**Accuracy (%)**	**Kappa Coefficient**
Original time series	80,0000	0,7714
Amplitude/Phase	51,2500	0,4429

Table 3 - Kohonen´s Self Organizing Maps classification comparison

Kohonen´s Self Organizing Maps		
Data set	**Accuracy (%)**	**Kappa Coefficient**
Original time series	78,7500	0,7571
Amplitude/Phase	65,0000	0,6000

Table 4 - Fuzzy ArtMap classification comparison

Fuzzy ArtMap		
Data set	**Accuracy (%)**	**Kappa Coefficient**
Original time series	78,7500	0,7571
Amplitude/Phase	46,2500	0,3857

Trying out different classification algorithms do not improve significantly the results with the classification accuracy ranging from 38 to 60% at its best in the Amplitude/phase as input vectors. These vector spaces proved inefficient to differentiate among forests (figure 2). The methodology of trying out different classification algorithms proved robust in this case, so that it can reinforce that the poor results come from the data set, not the algorithms. Work from Yu (2004) concludes that forest differentiation and classification can be successfully executed in the amplitude/phase space, however that work lacked statistical information regarding the accuracy of the mapping and the differentiation among forest cover was done with only four very different classes of vegetation: Decidual Forests, Evergreen Forests, shrubs and non-vegetation. Results in this work however suggest that the richness of the analyzed biome needs a dimensionality of information that can not be obtained in the amplitude/phase space. The original time series however prove efficient to differentiate vegetation with accuracy results ranging from 75.6% to 87.5%, but is a 36 dimension space. The amplitude/phase space however can not be relegated as an efficient tool in other instances. Work from Lacruz (2006) reveals that it can be a powerful tool to monitor vegetation and can be used as a tool for change detection.

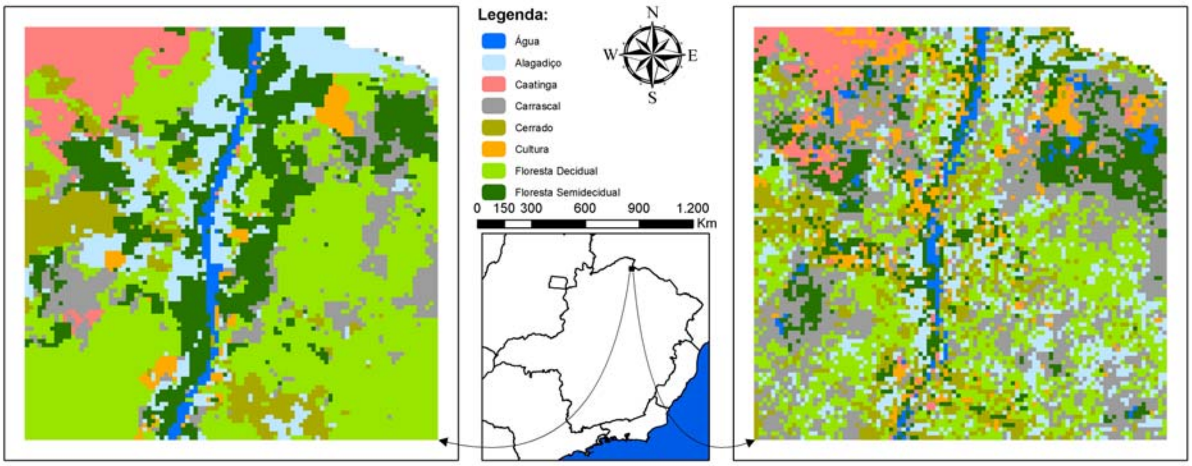

Figure 2 - Vegetation classification – left: original time series, right: amplitude /phase pace

4. Conclusion

Time series of MODIS NDVI can be successfully used to different forest types. The application of Harmonic analysis through the use of the HANTS algorithm can dramatically reduce the dimensionality of these time series. The use of this reduced data set has proved inefficient to generate correct mapping of forests. Results revealed that this methology of mapping forests in the amplitude/phase space does not capture the richness of information necessary for forest classification as seen in Carvalho (2001).

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