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Applying machine learning based on multiscale classifiers to detect remote phenology patterns in Cerrado savanna trees

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ABSTRACT

Plant phenology is one of the most reliable indicators of species responses to global climate change, motivating the development of new technologies for phenological monitoring. Digital cameras or near remote systems have been efficiently applied as multi-channel imaging sensors, where leaf color information is extracted from the RGB (Red, Green, and Blue) color channels, and the changes in green levels are used to infer leafing patterns of plant species. In this scenario, texture information is a great ally for image analysis that has been little used in phenology studies. We monitored leaf-changing patterns of Cerrado savanna vegetation by taking daily digital images. We extract RGB channels from the digital images and correlate them with phenological changes. Additionally, we benefit from the inclusion of textural metrics for quantifying spatial heterogeneity. Our first goals are: (1) to test if color change information is able to characterize the phenological pattern of a group of species; (2) to test if the temporal variation in image texture is useful to distinguish plant species; and (3) to test if individuals from the same species may be automatically identified using digital images. In this paper, we present a machine learning approach based on multiscale classifiers to detect phenological patterns in the digital images. Our results indicate that: (1) extreme hours (morning and afternoon) are the best for identifying plant species; (2) different plant species present a different behavior with respect to the color change information; and (3) texture variation along temporal images is promising information for capturing phenological patterns. Based on those results, we suggest that individuals from the same species and functional group might be identified using digital images, and introduce a new tool to help phenology experts in the identification of new individuals from the same species in the image and their location on the ground.

1. Introduction

Phenology, the study of natural recurring phenomena and its relation to climate (Schwartz, 2003), is a traditional science dedicated to the observation of the cycles of plants and animals and relate mainly to local meteorological data, as well as to biotic interactions and phylogeny (Staggemeier et al., 2010).

The leaf exchange patterns from leaf flush to senescence are key events to understand a range of ecosystem processes, considering its prominence on growth, water status, gas exchange, and nutrient cycling (Negi, 2006; Reich, 1995). The carbon balance and the productivity of terrestrial ecosystems are essentially defined by the dynamics of plant growing seasons (Keeling et al., 1996; Loustau et al., 2005; Rotzer et al., 2004), controlling spatial and temporal patterns of carbon and water exchange between forest and atmosphere (Schwartz et al., 2002; White et al., 1999).

Plant phenology has gained importance as the simplest and most reliable indicator of species responses in the context of global change research, stimulating the development of new technologies for phenological observation (Parmesan and Yohe, 2003; Richardson et al., 2009; Rosenzweig et al., 2008; Walther, 2004; Walther et al., 2002). Digital cameras have been successfully used as multi-channel imaging sensors, and the measurements of color change information (RGB channels) from digital images allow one to detect phenological changes in plants (Ahrends et al., 2009; Ide and Oguma, 2010; Kurc and Benton, 2010; Nagai et al., 2011; Richardson et al., 2007, 2009).

After quantifying the color channels, it is possible to estimate changes on phenological events, such as leaf flushing when analyzing the green channel, or leaf color change and senescence using values from the red channel (Ahrends et al., 2009; Richardson et al., 2009). However, image information from digital cameras is sparse for a highly diverse tropical forest, where one image may encompass dozens to more than a hundred species, compared to the low number of species in temperate vegetations.

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Another important feature that can be extracted from digital images is the spatial arrangement of the pixel intensities, known as texture (Torres and Falcão, 2006). The appearance of texture can help an observer to determine whether different regions from a digital image of a given vegetation have a same structure. Due to difficulties in measurement and interpretation, texture has been little used in phenology studies (Culbert et al., 2009).

We monitored a tropical Cerrado savanna vegetation to assess the reliability of digital images to detect leaf changes and validate the digital data with on the ground direct phenological observation (Alberton et al., 2012). In this paper, we investigate the use of machine learning based on multiscale classifiers to detect phenological patterns in a Cerrado savanna by using color and texture information of digital images. The key contribution of this study is the analysis of intra-species variations.

The primary goal of our research is to determine how good is the color change information to characterize the phenological pattern of a group of species. Moreover, we are interested in analyzing how promising is the temporal variation in image texture to distinguish different individuals that have similar spectral characteristics but different spatial patterns. Finally, we use machine learning based on multiscale classifiers to find similar textures in the digital image and we checked if they correspond to similar species or functional groups.

Based on those studies, we expect to open new venues on the automatic identification of plants from the same species or functional group using machine learning. Most of existing methods for species identification have focused on morphological features of a single organ (mainly leaf, rarely flower), often considering ideal conditions, such as noise-free images with a uniform background, taken at specific periods (Cope et al., 2012; Kumar et al., 2012).

Unlike previous works in the literature, we address the problem of identifying plant species by using phenology instead of morphometrics. Our strategy integrates a high degree of diversity in terms of locations, periods, and illumination conditions, which is a prerequisite to build modern plant identification systems.

A preliminary version of this work was presented at eScience 2012 (Almeida et al., 2012). Here, we include the analysis of texture information to characterize phenological patterns. The new reported results show the potential of texture change information for species identification.

The remainder of this paper is organized as follows. Section 2 presents our learning strategy and shows how to apply it to identify plant species. Section 3 describes materials and methods of our experimental protocol. Section 4 reports our experimental results and discuss how they can be applied in phenology studies. Finally, we offer our conclusions and directions for future work in Section 5.

2. Machine learning

In machine learning, classification is the task of assigning objects to one of several predefined *classes*. The input data for a classification task is a collection of records. Each record, also known as a *sample*, is characterized by a tuple $(\mathscr{F}, Y)$, where $\mathscr{F}$ is the attribute set and Y is a special attribute, called *label*, which indicates the class that belongs each sample (Tan et al., 2005).

The attribute set $\mathscr{F}$, also known as a *feature vector*, is a sequence of continuous or discrete values obtained from measures over a given object and it is used for computationally describing each sample concerning a specific property. The label, on the other hand, must be a discrete attribute (Tan et al., 2005).

A *detector* or *classifier* is a systematic approach to building classification models from an input data set. Each technique employs a *learning strategy* to identify a model that best fits the relationship between the feature vector and label of the input data (Tan et al., 2005).

For that, a *training set* consisting of records whose labels are known must be provided. The training set is used to build a classification model, which is subsequently applied to predict the labels of records it has never seen before (Tan et al., 2005). For more details concerning machine learning concepts, refer to (Alpaydin, 2010; Rostamizadeh and Talwalker, 2012).

In this paper, we use machine learning to detect phenological patterns. For this purpose, we adopted the *multiscale classifier* (MSC) approach (dos Santos et al., 2012b) to learn phenological patterns and build phenological pattern detectors. It was chosen due to its ability of combining different features by weighting the ones more suitable for each plant species. Moreover, it also allows the combination of features from different segmentation scales, which increases the power of the final detector (dos Santos et al., 2012a).

2.1. Multiscale classifier

The *multiscale classifier* (MSC) (dos Santos et al., 2012b) is a learning strategy based on boosting of weak learners. It is based on the Adaboost algorithm proposed by Schapire (1999), which builds a linear combination of weak classifiers to compose a final strong one. A weak learner is a classifier slightly better than the random. Boosting-based classification strategies have been extensively used in applications that need to combine a large sets of different features or classifiers (Grabner and Bischof, 2006; Lechervy et al., 2013; Viola and Jones, 2001).

Let H be a hierarchy of segmented regions, P_λ is a partition, which is the segmentation result at a given scale λ. A partition P is obtained by cutting the hierarchy H. In this sense, $R \in P$ refers to any region R that belongs to the partition P. The MSC aims at assigning a label ($+1$, for relevant class; and -1, otherwise) to each pixel p of P_0 taking advantage of various features computed on regions of various levels from a segmentation hierarchy H. The final classifier is a linear combination $MSC(p)$ of T weak classifiers $h_t(p)$:

$$MSC(p) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(p)\right), \tag{1}$$

where α_t is the weight assigned to the weak classifier $h_t(p)$ at the iteration t.

The training consists of testing *weak learners* in a sequence of rounds $t = 1, \ldots T$. Each weak learner builds a weak classifier that reduces the expected classification error of the final classifier. For each round t, MSC selects the weak classifier that most decreases the error.

The algorithm keeps a set of weights over the training set. The weights can be understood as a measure of difficulty of each sample. The pixels start with the same weights. But along the rounds, the weights of the misclassified pixels are increased. Thus, the weak learners are forced to focus on the most difficult samples. We note $W_t(p)$ the weight of pixel p in round t, and $D_{t,\lambda}(R)$ the misclassification rate of region R in round t at scale λ which is the mean of the weights of its pixels:

$$D_{t,\lambda}(R) = \left(\frac{1}{|R|}\sum_{p \in R} W_t(p)\right). \tag{2}$$

Algorithm 1 presents the training process of the MSC. Let $Y_\lambda(R)$, the set of labels of regions R at scale λ, be the training set. In a series of rounds $t = 1, \ldots T$, for all scales λ, the weight of each region $D_{t,\lambda}(R)$ is computed (line 3). The selection of regions is based on this piece of information to create a subset of labeled regions $\widehat{Y}_{t,\lambda}$ (line 6). This subset is used to train weak learners: each features $\mathcal{F}$ at scale λ (line 9). Each weak learner produces a weak classifier $h_{t,(\mathcal{F},\lambda)}$ (line 10). The algorithm then selects the weak classifier h_t that most reduces the error Err_{h_t} (line 12). The level of error of h_t is used to compute the coefficient α_t, which indicates the degree of importance of h_t in the final classifier (line 13). The selected weak classifier h_t and the coefficient α_t are used to update the weights of the pixels $W_{(t+1)}(p)$ which can be used in the next round (line 14).