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Histogram-based spatio-temporal feature classification of vegetation indices time-series for crop mapping

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ABSTRACT

Classification of time-series of vegetation indices (VIs) can be a reliable strategy for identifying and monitoring different crop types. Recently, with the advent of new sensors, the time-series data with high spatial and temporal resolutions have become widely available and used for constructing various VIs time-series. These high-resolution time-series, in addition to temporal information about the crops' phenology, contain valuable information about the spatial patterns of croplands. This information can be used to increase the performance of crop classification. In order to properly extract both spatial and temporal information from the time-series of VIs, we proposed the concept of histogram-based spatio-temporal (HST) features. These features represent each pixel in a time-series by the histogram of its spatio-temporal neighborhood. The HST features, like any other histogram-based features, are characterized by high dimensionality and sparseness. Consequently, the common classification algorithms cannot be employed for their classification. To address this issue, we presented Support Vector Machines (SVM) using an intersection kernel, which is specifically proposed for classification of histogram-based features. Time-series of three different vegetation indices, namely, Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Red Edge Normalized Difference Vegetation Index ($NDVI_{RE}$) were considered to evaluate the performance of the HST features. The results of experimental tests showed that the HST features by yielding the overall accuracy of 88.31%, 87.27% and 84.36% for $NDVI_{RE}$, NDVI, and SAVI respectively are much more informative than other textural features used for comparison. Moreover, we provided a detailed analysis of the performance of the HST features concerning the size of the spatio-temporal neighborhood and the number of histogram's bins.

1. Introduction

Crop identification plays a crucial role in various agricultural applications. Because knowledge about the crops type is needed as the base information for various analyses such as crop acreage estimation, yield forecasting, estimation of water requirements, and assessment of food security (Li et al., 2014; Löw et al., 2015b; Simonneaux et al., 2008). When remote sensing (RS) imagery is used to identify different crop types, the information content of a single image is often deemed insufficient. This lack of information is primarily due to the dynamic spectral patterns of crops throughout their growth cycle as well as the high spectral similarity among certain types of crops (Löw et al., 2015a). Classification of different Vegetation Indices (VIs) time-series is one approach to address these issues. The VIs can increase the performance of classification since their corresponding spectral bands contain the most significant information of the crops' spectra (Gerstmann et al., 2016). Moreover, the calculation of VIs over the time provides supplementary information about varying crops' spectral behavior and phenology (Meroni et al., 2014; Verhegghen et al., 2014).

Medium to low-spatial resolution sensors (e.g., MODIS, AVHRR, and SPOT-Vegetation) have a high temporal resolution and as such, have frequently been used for constructing satellite images time-series. The vegetation indices time-series of these sensors have been very beneficial for agricultural and environmental applications at regional and global scales. Geerken et al. (2005) proposed a method to classify rangeland vegetation over Syria using the NDVI time series of SPOT-Vegetation

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data during the years 2000 and 2001. Spruce et al. (2011) extracted MODIS NDVI time-series, from 2001 to 2016, to detect forest defoliation by a gypsy moth outbreak at a regional scale in the United States. Zhou et al. (2013) also constructed the time-series from different MODIS spectral bands combinations and NDVI data to evaluate the vegetative and non-vegetative land-cover classification at regional scales. Jamali et al. (2014) extracted NDVI from Global Inventory Modeling and Mapping Studies (GIMMS) and used them to classify vegetation trends in North Africa from 1982 to 2006. However, for most annually cropped lands, field sizes are much smaller than the spatial resolution of these sensors. Consequently, this class of sensors is typically not suitable to classify crops at the field scales.

The new generation of earth observation sensors (e.g., RapidEye, Sentinel-2, Planet Dove and SkySat) have both high spatial and temporal resolutions and thus can be exploited to provide high spatial resolution time-series for a range of natural resources applications, including field-scale agricultural classification. Time-series from these sensors contain useful information about the evolution of crop status during the growing season and the information concerning the spatial distribution of their reflectance. This information, if correctly extracted and modeled, can further boost the performance of the field-scale agricultural analysis and classification.

Although numerous studies have been conducted on crop classification using high-resolution time-series of VIs (Ali et al., 2015; Bach et al., 2012; Kross et al., 2015; Shang et al., 2015), only a few have fully exploited both spatial and temporal information at the same time. For example, a spatio-temporal feature extraction method was proposed in (Wagenseil and Samimi, 2006) for NDVI time-series extracted from the SPOT-Vegetation sensor. In their study, the authors used the amplitude and the phase information obtained from the Fourier series of each pixel of the time-series as the input features. Since the Fourier series assumes the signal to be periodic and sinusoidal, the authors used the time-series of two growing seasons in their study. After estimating these features, averages and standard deviations were calculated using a moving window and subsequently used as the spatio-temporal features for the classification. In another study, object-based image analysis was used to extract the spatio-temporal features from time-series of multispectral Formosat-2 imagery (Petitjean et al., 2012). In this method, the images were initially segmented into some homogeneous regions (i.e., objects), and a time-series was then constructed by using the features extracted from each object over the entire period of the time-series. Although this method showed promising results, its implementation is significantly confined by the definition of the objects. Moreover, tracking the objects between different dates would be very challenging as the shape and position of the object changes over time. Another method, based on the grouped frequent sequential pattern extraction, was proposed for extracting spatio-temporal features from the NDVI time-series of the SPOT sensor in (Julea et al., 2012). In this method, after obtaining a symbolic representation of the time-series, a set of connected pixels were extracted which shared similar patterns over time. The patterns were characterized by the temporal change of the symbols. Although these patterns cannot be used directly for classification, they reveal useful information in support of agricultural monitoring.

Despite the acceptable performance of these methods, some issues confine their application for crop classification and mapping. Thus, this paper proposed a novel method to derive efficient spatio-temporal features from a time-series of vegetation indices for crop classification. The new features, called Histogram-based Spatio-Temporal features (HST), are defined based on the local histogram extracted from a spatio-temporal neighborhood of each pixel for a time-series. As a result of using local histograms of data, these features represent each pixel through the marginal local distribution of the pixels in a spatio-temporal neighborhood of that pixel. Consequently, they not only model the spatial and temporal texture of the data but are also more robust to noise. Furthermore, due to extracting histograms from a spatio-temporal neighborhood, the performance of these features are less affected by the presence cloud and shadows in the images.

The HST features inherit the characteristics of the histogram-based features such as nonlinearity, sparseness, high dimensionality and transition invariance (Liu and Wang, 2003; Zhang et al., 2005). Consequently, most classification methods cannot be used to classify these features. To address this issue, we presented the Histogram Intersection Support Vector Machine (HISVM) algorithm. The HISVM is an SVM, trained with the Histogram Intersection (HI) kernel. This kernel is a positive-definite kernel, and its calculation is computationally inexpensive. The HI kernel can properly handle the high-dimensionality and sparsity of histogram features (Barla et al., 2003; Zhang et al., 2005).

The histogram-based features have been used in many studies in the machine learning literature (Barla et al., 2003; Chapelle et al., 1999; Liu and Wang, 2003; Zhang et al., 2005). More recently these features have been used for context-based image retrieval and classification of morphological attribute profiles extracted from high-resolution satellite images (Battiti et al., 2016; Demir and Bruzzone, 2015, 2016). However, to the best of our knowledge, this is the first time that these features have been modified as spatio-temporal features in time-series analysis.

The main contribution of this paper is to propose a novel spatio-temporal features for time-series data classification. Moreover, we analyzed the key parameters that affect the performances of these features. Finally, we presented HISVM algorithm for the classification of these features and compared their classification results with those of other common temporal and spatial features.

2. Methodology

Assume that we are provided with n co-registered images with dimensions of $m_1 \times m_2$, acquired over the same area at n different acquisition times, denoted by $T_1 < T_2 < \ldots < T_n$. The results of extracting a vegetation index from these images will be a univariate time-series of images with a dimension of $m_1 \times m_2 \times n$. Here the image of the vegetation index, extracted from the image acquired at the time T_i, was called as time-frame and denoted by I_{T_i}, $i = 1, \ldots, n$. The values of the pixel located at p^{th} row and the q^{th} sample of all time-frames ($x_{pq}^{T_i}$, $i = 1, \ldots, n$) can be considered as a time-series that can be represented by a vector $\mathbf{x}_{pq} = (x_{pq}^{T_1}, x_{pq}^{T_2}, \ldots, x_{pq}^{T_n})^T$. Assume that N_c land-cover classes can be identified form the time-series data. From these classes, the set $D = \{\mathbf{s}_i, y_i\}_{i=1,\ldots,m}$, consisting of m samples with their corresponding labels y_i, were extracted as the training set. The samples in this set, represented by $\mathbf{s}_i$, are time-series associated with m different pixel locations. In the following subsections, a method for extracting the HST features is first introduced, followed by the HISVM classification.

2.1. Histogram-based spatio-temporal feature extraction

In order to extract the histogram-based spatio-temporal features, the temporal and spatial neighborhoods need to be defined. We adopted a time interval with a fixed window size of w_t around each acquisition date, as its temporal neighborhood. In other words, for the i^{th} time-frame, this temporal neighborhood, denoted by Tn_i, contains the available time-frames acquired within a time interval $S(i)$. This time interval includes all the time-frames acquired from w_t before to w_t after the i^{th} acquisition date. The Tn_i can be defined using the following set:

$$Tn_i = \{I_{T_i}: T_i \in S(i)\} \tag{1}$$

where $S(i)$ can be estimated as: