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A novel spectrum enhancement technique for multi-temporal, multi-spectral data using spatial-temporal filtering

Hessah Albanwan[a], Rongjun Qin[a,b,*]

[a] Geospatial Data Analytics Laboratory, Department Civil, Environmental and Geodetic Engineering, The Ohio State University. 2036 Neil Avenue, Columbus, OH, USA
[b] Department of Electrical and Computer Engineering; The Ohio State University. 2015 Neil Avenue, Columbus, OH, USA

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ABSTRACT

Time-sequence remote sensing images are usually captured under varying acquisition conditions due to atmospheric differences, lighting condition, humidity etc. Comparing the spectral values of the well-registered images taken at a different time is a complicated issue due to the non-linear spectrum distortion caused by these effects. Atmospheric correction can eliminate part of the errors, while precisely removing it requires many other in-situ data such as the weather condition and optical aerosol depth. We propose an algorithm that performs spatial-temporal inferences that correct the spectral values through a data-driven approach - we developed a simple 3D spatiotemporal filtering method that uses the time-sequence imagery themselves to homogenize the spectral property of similar objects while being heterogeneous to objects with significant differences. We have performed extensive experiments using medium resolution Landsat dataset and high-resolution Planet imagery, by evaluating the classification results from both classic machine learning (sample selected from the current image) and transfer learning (samples selected from one dataset and applied to the other dataset). The experiments results show that the proposed 3D spatiotemporal filter can improve the accuracy of classification using transfer learning by ≈5%, ≈15%, and ≈2%. We have also demonstrated that the enhanced time-sequence image offers much better change detection outputs using just a simple image differencing method. The improved results in typical remote sensing tasks indicate our proposed method being effective for time-sequence data preprocessing.

1. Introduction

1.1. Background

Satellite remote sensing images are a great source of information to study the land, water, atmosphere and natural phenomena. Time series analysis of satellite images acquired over time is an important field of study in remote sensing since multi-temporal data can be used to extract the plant phenology, and track human activities and dynamics of the urban/natural systems. However, one of the most critical issues of analyzing multi-temporal satellite images is the requirement of radiometric/spectral consistence for correlating, comparing, and processing the data. Very often, the acquired images vary in their appearances, due to different lighting conditions such as the sunlight intensity and direction, atmospheric scattering and absorption, metrological conditions such as the existence of clouds, snow, and rain. In addition, the changing condition of satellite sensors due to aging and operating environments will also cause spectral distortion and imaging qualities. Therefore, one of the consistent endeavors is to minimize such effects and homogenize the spectral reflectance of similar objects on the ground (Paolini et al., 2006; Lu et al., 2011), which is subsequently beneficial to boost the performance and success of relevant applications that utilize time series remote sensing data, e.g. change detection, spatial-temporal analysis and land-cover and land-use change mapping (LCLUC).

Image classification is regarded as an effective way for evaluating the radiometric/spectral quality of remote sensing images in many of the existing works (Paolini et al., 2006), and the accuracy of the classification tells to which extent the images can be used for automated interpretation. A classification framework examines the spectrum of an image through:

(1) Intra-class similarity: The spectrum of a class should be similar, such that the class can be uniquely characterized.
(2) Inter-class dissimilarity: The spectrums of two different classes should be different enough to be identified as different classes of objects.

* Corresponding author at: Geospatial Data Analytics Laboratory, Department Civil, Environmental and Geodetic Engineering, The Ohio State University. 2036 Neil Avenue, Columbus, OH, USA. Tel.: 1 614 292 4356.
E-mail address: qin.324@osu.edu (R. Qin).

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Theoretically, earth surfaces with different material should reflect different spectral curves. Practically, such intra-class similarity and inter-class dissimilarity are often saturated by factors such as resolution, image noise, and atmospheric absorption. An effective and actively investigated approach to resolve such ambiguities is to introduce spatial-spectral classifications, where the spatial distribution of spectrum value around a pixel was taken into account (Fauvel et al., 2012, 2013; Li et al., 2014; Bernard et al., 2012; Bernabé et al., 2014). However, when time-series data are being processed, a more important question to these two factors is, whether the same level of intra-class similarity and inter-class similarity can be obtained consistently through time? It is very often observed that the classification results vary greatly between two temporal images of the same location, even with a similar set of training data. Such discrepancy is reflected by the fact that: (1) the pixel values of the same ground unit are different; (2) the difference of neighboring pixels of the same ground unit is different. Temporal images taken under different acquisition conditions are highly disparate, the resulting pixel values/spectrums of which are too complex to be modeled through simple linear/quadratic radiometric correction methods.

In multi-temporal data analysis, image classification is usually applied through the temporal datasets, either independently or concurrently to derive the spatial-temporal dynamics of the land classes. It is usually time-consuming to generate training samples for each dataset for classification, and one approach to avoid time-consuming training sample collection process, termed transfer learning, is to apply classifiers trained from one dataset to other datasets (Dai et al., 2009). This approach usually requires a process of performing feature space transformation to fit the reference classifier to the target image (Arnold et al., 2007), and this is due to the dramatic non-linear differences between image spectrums/pixel values of the same class of objects. Such feature space transformation, usually apply a parametric model with fixed degree of freedom (Duan et al., 2012; Shao et al., 2015; Pan et al., 2011), which might be hard to model the complex image radiometric/spectrum discrepancies brought by the image acquisition conditions.

In this paper, we develop a simple but effective non-parametric approach to directly correct the relative radiometric discrepancies of multi-temporal, multi-spectral remote sensing images. The approach is termed 3D spatiotemporal filter, which simultaneously incorporates temporal and spatial aspects of time series multispectral data into an edge-aware filter: it homogenizes similar spectrums while keeping dissimilar spectrums disparate. The unique characteristic of this approach is that it neither requires any prior information nor assumes a fixed parametric model for data correction. The enhanced (corrected) multi-temporal dataset will allow classifier trained from one dataset, to be directly used to another dataset. The remainder of our work is organized as follows: Section 1.2 reviews the relevant methods of relative radiometric correction. Section 2 introduces the proposed 3D spatiotemporal filter to enhance the radiometric qualities of multi-temporal datasets, and then introduces our evaluation methods based on classic machine learning and transfer-learning based classification, with an additional change detection experiment. It also includes a comparative study with other state-of-the-art relative radiometric normalization approaches. The experimental results and the discussion are presented in Section 3, with the conclusions drawn in Section 4 discussing the pros and cons of the proposed method and future improvements.

1.2. Related works and the proposed method

Radiometric correction methods were normally presented as a part of the preprocessing steps for tasks such as image classification and change detection. While being critical to the classification and change detection results, their impact have rarely been comprehensively discussed (Paolini et al., 2006; Vanonckelen et al., 2013). Our proposed method aims to enhance the spectral quality of the multi-temporal for spatial-temporal image analysis, specifically for classification and change detection. In this section, we will review the existing efforts in radiometric correction and pinpoint the existing challenges of classification and change detection associated with it.

1.2.1. Radiometric correction using time series analysis

The radiometric consistency of multi-temporal images is often affected by metrological conditions, the illumination differences, and satellite sensor conditions. Traditional remote sensing atmospheric correction techniques using radiative transfer models have demonstrated success in reflectance recovery (Berk et al., 1999), while to utilize such methods accurately requires much in-situ information such as AOD (aerosol optical depth) (Schroeder et al., 2006), camera looking angle (Lin et al., 2004; Chander et al., 2009), sensor calibration parameters (Chander et al., 2009), temperature, humidity, etc. The recovery of surface reflectance is important when deriving the actual physical property of the earth surfaces (Gordon & Wang, 1994; Kaufman et al., 2001; Tucker & Sellers, 1986), while not necessary for applications such as image classification and change detection. Particularly, the required in-situ information might not be always available and increases the workload and expenses. Therefore, it is important to find simple and effective ways to correcting non-linear spectral reflectance prior to performing classification and change detection.

Radiometric correction for multi-temporal images can be either absolute of relative. The absolute radiometric correction refers to the recovery of the actual surface reflectance (atmospheric correction), normally achieved through the process of atmospheric correction, which is complicated and requires additional in situ measurements for accurate correction (Moran et al., 1992; Slater et al., 1987; Vermote & Kaufman, 1995). The relative radiometric correction and normalization (RRN) use one image as a reference to adjust and relate the radiometric properties of the rest of the images (Xu et al., 2012). The relative methods (relative correction or normalization) are more preferred as it does not require additional observations except for the images themselves. This normally refers to the correction of a multiplicative and additive intensity change, and the correction parameters can be either estimated through a few reference pixels or all pixels and patches (El Hajj et al., 2008; Yang and Lo, 2000). In the process of estimating the correction parameters (scale and offset, relevant to multiplicative and additive intensity change), blunder pixels, such as clouds or significantly changed areas need be eliminated (Paolini et al., 2006). However, the radiometric difference between temporal images is sometimes too complex to be simply modeled as linear or quadratic functions. For instance, the widely used Dark Object Subtraction (DOS) algorithm (Chavez, 1988) is a relative correction method that was developed particularly for haze reduction, while this method assumed the presence of the haze over the entire image, and potentially leads to "over-correction" – areas not affected by the haze will lose its fidelity. One of the most relevant work is the spatiotemporal filter used in our previous work (Qin et al., 2016), where the height information is incorporated in the temporal domain to reduce the noises of the building classification map. However, this work did not incorporate the spectrum component in the temporal direction. Moreover, the selection of a single reference image for relative correction methods can be challenging. Several conditions govern the choice of the reference image such as having minimum spectral changes over the time (e.g. minimum vegetation) and ensuring the regions be flat to minimize shadows or any blockage in the scene, in addition to having a clear and atmospheric effect free images (Gore Biday & Bhosle, 2010; Rahman et al., 2015). Since a clear noise-free image as a reference is very difficult to obtain, it would be more beneficial and flexible to use the image pixels adaptively in the dataset for correction.

1.2.2. Supervised image classification and transfer learning

Image classification is a heavily investigated, yet still very active research topic. It directly yields land-cover and land-use maps for local