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Sparse-based reconstruction of missing information in remote sensing images from spectral/temporal complementary information

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ABSTRACT

Because of sensor failure and poor observation conditions, remote sensing (RS) images are easily subjected to information loss, which hinders our effective analysis of the earth. As a result, it is of great importance to reconstruct the missing information (MI) of RS images. Recent studies have demonstrated that sparse representation based methods are suitable to fill large-area MI. Therefore, in this paper, we investigate the MI reconstruction of RS images in the framework of sparse representation. Overall, in terms of recovering the MI, this paper makes three major contributions: (1) we propose an analysis model for reconstructing the MI in RS images; (2) we propose to utilize both the spectral and temporal information; and (3) on this basis, we make a detailed comparison of the two kinds of sparse representation models (synthesis model and analysis model). In addition, experiments were conducted to compare the sparse representation methods with the other state-of-the-art methods.

1. Introduction

Due to the sensors being out of working order (e.g., Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) band 6 (Li et al., 2014), the Landsat ETM+ SLC-off problem (Zeng et al., 2013), the row anomaly problem of Aura OMI (Yan et al., 2012)) or in a cloudy atmosphere, the involved regions in remote sensing (RS) images often have invalid information, which we call missing information (MI). It is noteworthy that only passive RS images (visible and infrared) are affected by the atmosphere. MI greatly reduces the availability of RS images. Thus, reconstruction of the MI of RS images is a hot topic in the RS field. It is in fact similar to the old and well-known inpainting (Bertalmio et al., 2000) problem in the image processing field. To date, a number of methods have been aimed at image inpainting, e.g., interpolation (Kokaram et al., 1995), partial differential equations (PDE) (Bertalmio, 2006), total variation (TV) (Chan et al., 2005), and the Huber–Markov method (Shen and Zhang, 2009). For small and sparse missing areas of RS images, these methods can obtain a satisfactory recovery effect. However, they are not able to reconstruct large missing areas. These methods are all based on spatial complementation. Unfortunately, the MI area is usually large in RS images. As a result, the spatial complementation based methods cannot successfully reconstruct the MI of RS images.

For multispectral RS images, the bands are correlated with each other in the spectral domain, and it is the band-to-band correlation which we call spectral complementation. Generally speaking, the spectral complementation plays an important role on the condition that (for multispectral images) some bands have MI and others are intact. The authors in Li et al. (2014), Wang et al. (2006), Rakwatin et al. (2009), Shen et al. (2011), and Gladkova et al. (2012) made the best use of spectral complementation to reconstruct the corrupted band by modeling the spectral relationship between the corrupted band and the other good bands (one or more). As a result of the effective mathematical or physical restrictions, they reduced the error of the polynomial fitting. Cheng et al. (2014) proposed a variation-based method by combining the strengths of a TV method and a nonlocal method. Although this method aims to reconstruct a multispectral image in which all the spectral bands have the same MI, it is still suitable for the case stated here. Additionally, Shen et al. (2014) proposed a sparse representation based method which adaptively weights the intact bands

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according to the spectral importance. In short, the spectral complementation based methods have an advantage over the spatial complementation based methods when coping with large-area MI. However, if the atmosphere is cloudy and rainy, the RS images acquired in the visible and infrared ranges will be occluded by clouds. In this case, the spectral complementation is ineffective.

Correspondingly, a number of scholars have resorted to other sources of complementary information. For RS images (over the same region) acquired from different periods, they are correlated in the temporal domain, and it is the image-to-image correlation which we call temporal complementation. Hereafter, the images from different periods and over the same region are referred to as "multitemporal images". Temporal interpolation (Inglada and Garrigues, 2010) and filters (Jakubauskas et al., 2001; Chen et al., 2004; Roerink et al., 2000) are the most basic reconstruction methods; however, in order to obtain a satisfactory reconstruction, they are dependent on a long time series of data. Regression analysis (Zeng et al., 2015), mosaicing or completion (Helmer and Ruefenacht, 2005; Lin et al., 2014; Cheng et al., 2014), and geostatistical methods (Zhang et al., 2009) are simple and common algorithms which just use a reference image from another period; however, they sometimes do not obtain a good effect in the junction of a missing region and good region. Recently, sparse representation based methods (Li et al., 2014; Lorenzi et al., 2013) have also been used in this field and have obtained promising results. Unfortunately, the temporal complementation based methods have a fatal flaw in that once the multitemporal images show a significant land-cover change, the methods are no longer applicable.

In recent years, researchers have verified that the sparse representation based methods are appropriate for recovering large-area MI (Guillemot and Le Meur, 2014), which has inspired our interest. Firstly, we make a simple review of sparse representation, as follows.

- **Sparse representation.** Sparse representation was first proposed in the 1980s (von zur Gathen and Kaltofen, 1985; Coppersmith and Davenport, 1985; Pissanetzky, 1984), and is a representation that accounts for most or all the information of a signal by a linear combination of only a small number of elementary signals, called atoms (Gemmeke et al., 2011). In the 1990s, Mallat and Zhang (1993) proposed the concept of the overcomplete dictionary to initiate a new development stage. Sparse representation has found applications in numerous domains and tasks, such as image inpainting, denoising, super-resolution, fusion, classification, and target detection. According to the crude estimation of the ISI Web of Science, there have been more than 4000 papers related to sparse representation (Nam et al., 2013). To the best of our knowledge, Olshausen and Field (1996) first introduced sparse representation into the field of natural image processing, and since then it has developed into two main classes: synthesis models and analysis models.
- **Synthesis models.** As the name implies, synthesis models synthesize a signal $x \in \mathbb{R}^m$ by the multiplication of two components, i.e., $x = D\alpha$, where $D \in \mathbb{R}^{m\times n}(m < n)$ is an overcomplete dictionary (i.e. D is a matrix with m rows and n columns) and $\alpha \in \mathbb{R}^n$ is the representation coefficient. The columns of D are called dictionary atoms. This expression is called a sparse representation, on the condition that the vector α is sparse, i.e., $\|\alpha\|_0 = k \ll n$, meaning that the number of nonzero elements (k) is far less than the total number (n). In other words, the signal x can be represented as a sparse linear combination of the k atoms from the redundant dictionary (Aharon et al., 2006; Elad and Aharon, 2006). The last decade has witnessed a great amount of investigation into synthesis models, which attempt to obtain a better sparse approximation to the real signal. To date, synthesis models have been successfully applied to image denoising (Elad and Aharon, 2006), super-resolution (Rehman et al., 2012; Jianchao et al., 2010), inpainting (Mairal et al., 2008; Fadili et al., 2009), and deblurring (Weisheng et al., 2011). Relatively speaking, they are a mature class of model with solid theoretical foundations and extensive applications.
- **Analysis models.** These models take an analysis point of view (Rubinstein et al., 2013). Differing from the synthesis models, which decompose the signal to get a redundant dictionary and sparse coefficients, analysis models aim to gain a sparse outcome by multiplying the signal by an analysis operator (dictionary). Given an analysis dictionary $\Omega \in \mathbb{R}^{p\times m}(p > m)$, (i.e. Ω is a matrix with p rows and m columns), the analyzed outcome is $y = \Omega x \in \mathbb{R}^p$. The representation y should be sparse (or we say "cosparse"), meaning $\|y\|_0 = p - l \ll p$ (l denotes the number of zeros in y). These zeros carve out the low-dimensional subspace that the signal belongs to Rubinstein et al. (2013). Analysis models have been preliminarily and empirically applied to the restoration of information, including signal and digital image recovery (denoising) (Yaghoobi et al., 2013; Ophir et al., 2011; Yaghoobi et al., 2012; Giryes et al., 2011), and the MI recovery of natural images (Hawe et al., 2013). To the best of our knowledge, analysis models have not yet been used in the processing of RS images. Compared to the synthesis models, they are a young class of model.

Among the methods above, the authors of Shen et al. (2014), Li et al. (2014), and Lorenzi et al. (2013) adopted sparse representation based methods, but not analysis-based methods. In this paper, we propose an analysis-based method. We also want to know, between the synthesis and analysis models, which is the better approach to reconstruct missing RS information? In addition, is it better to extract the complementary information from both the spectral and temporal domains? We attempt to answer these questions in this paper.

This paper makes three contributions to the reconstruction of missing RS information: (1) we introduce an analysis model to reconstruct the MI in RS images; (2) a detailed comparison is made between the synthesis and analysis models; and (3) the spectral and temporal complementary information is jointly used.

The rest of this paper is organized as follows. In Section 2, we present the algorithms used for reconstructing the MI of RS images, based on synthesis and analysis models, respectively. Section 3 provides the specific comparisons between the two models, using only multispectral images, using only multitemporal images, and using both multispectral and multitemporal images. Finally, the conclusions are drawn in Section 4.

2. Algorithms

As stated previously, the sparse representation based methods are suitable for the reconstruction of large-area MI. To date, a number of researchers have proposed sparse-based reconstruction methods for RS images (using synthesis models) (Shen et al., 2014; Li et al., 2014; Lorenzi et al., 2013). However, to the best of our knowledge, analysis models aimed at recovering the MI of RS images have not been investigated. Accordingly, we propose an analysis model based algorithm in this paper. For RS images, the spectral and temporal complementation lays a solid foundation for the reconstruction of the MI. However, the present methods use only one kind of complementation to reconstruct the MI of RS images. Our other goal is to explore whether the two