Signal Processing ▮ (▮▮▮▮) ▮▮▮–▮▮▮

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Sparse representation based pansharpening with details injection model

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A R T I C L E   I N F O

Article history:
Received 9 August 2014
Received in revised form
15 November 2014
Accepted 12 December 2014

Keywords:
Sparse representation
Dictionary learning
Pansharpening
Details injection

A B S T R A C T

Sparse representation based pansharpening attracts a lot of interests, which formulates the pansharpening as a compressive sensing reconstruction problem. In this paper, a new pansharpening method based on sparse representation with details injection model is proposed. Differently from the existing sparse representation based methods, the proposed method adopts the ARSIS concept instead of the compressive sensing reconstruction, and the pansharpened image is created by the details injection. Therefore, the prior assumption is not required to define the reconstruction model. The proposed method applies the sparse representation based image decomposition to extract the spatial details from the panchromatic image. Meanwhile, only the panchromatic image in the à trous wavelet domain is used to learn the dictionary that makes the proposed method more practical. The quantitative results and visual evaluation on the QuickBird and WorldView-2 data show that the proposed method is comparable or even superior to the existing sparse representation based methods and some conventional methods.

1. Introduction

Image fusion is an image processing technique that integrates the complementary information from multiple images acquired by different sensors. The fused image is useful for further image analysis and applications. Pansharpening is a special image fusion which merges a high resolution panchromatic (PAN) image and a low resolution multispectral (MS) image into a high resolution MS image. Pansharpening not only improves the quality of image, but also overcomes the physical and technical limitations of satellite sensors. The pansharpened image has great potential in lots of remote sensing applications [1,2]. Many methods have been extensively researched and reported to address the pansharpening problem. Among them, the component substitution and the multiresolution analysis (MRA) are two commonly used methods.

The component substitution method is based on pixel transformation of the MS spectral bands. The common framework of component substitution is that a component of MS image, generated by a certain pixel transformation, is substituted by the PAN image. The representative component substitution method is based on the intensity hue saturation (IHS) transformation [3], which replaces the intensity component of MS image as the PAN image. The earliest IHS based method only deal with the three spectral bands pansharpening problem. However, most satellites can provide the MS images with more than three spectral bands, such as the QuickBird and WorldView-2. To address this issue, Tu et al. [4] reports a fast IHS (FIHS) based method which adds the response of near infrared band to calculate the intensity component. The FIHS method has been improved through different strategies, for example, with spectral adjustment [4], with a tradeoff parameter to control the spatial resolution and spectral resolution [5], and with edge-adaptivity [6]. In addition, some other transformations have also been applied into the component substitution based methods, such as the

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http://dx.doi.org/10.1016/j.sigpro.2014.12.017
0165-1684/© 2014 Published by Elsevier B.V.

principal component analysis (PCA) [7] and the Gram–Schmidt (GS) [8]. The component substitution method can preserve spatial information effectively, but may suffer from the inconvenience of spectral distortion.

The MRA is another popularly used group of pansharpening methods. The MRA based methods can be accommodated within the ARSIS concept [9]. The ARSIS concept assumes that the missing spatial information of low resolution MS image is linked to the high frequencies of PAN image [9]. The well-known MRA methods are based on the discrete wavelet transform [10] and the à trous wavelet transform [11–13]. In contrast, the à trous wavelet transform is shift invariant without decimation, and can generate a better pansharpened image. The AWRGB [11] is the original à trous wavelet transform based method for three spectral bands. Since then, the AWRGB is improved with some adaptive details injection model. The representative one is the additive wavelet LHS (AWL) method, which consists in injecting the spatial details into the luminance component of MS image [11]. The proportional AWL (AWLP) method extends the AWL method for more than three spectral bands [12]. In addition, the details injection model with PCA [14] and context-based decision (CBD) [15] have been studied to preserve the spectral information. Furthermore, some other MRA has also been exploited, such as the Laplacian pyramid [16] and the contourlet transform [7]. Compared with the component substitution method, the MRA based method can reduce the spectral distortion more effectively. However, one MRA can only extract the spatial details with the given structure, and may be not effective for all structures.

Recently, sparse representation has been applied into pansharpening, and receives significant attentions. Li and Yang [17] give the first attempt, which reconstructs the pansharpened image from the low resolution MS image and the PAN image by the compressive sensing. In the Li and Yang's method [17], the raw high resolution MS patches are used to construct the high resolution MS dictionary. However, in practical applications, the high resolution MS image is unavailable. To address this issue, some dictionary learning methods have been developed to infer the high resolution MS dictionary, such as the joint dictionary learning [18,19], learning dictionary from the PAN image [20] and learning dictionary from the primary pansharpened image [21]. In addition, Palsson et al. [22] applies the over-complete multiscale transforms to ensure the sparsity of high resolution MS image. Similar to Li and Yang's method [17], the modified methods [18,19,21] still rely on some assumptions to define the compressive sensing reconstruction model, such as, the low resolution MS image is assumed as the degraded version of high resolution MS image, and the PAN image is expressed as the linear combination of high resolution MS bands. These assumptions still restrict the performance of these sparse representation based approaches.

In this paper, a novel sparse representation based pansharpening method, exploiting the details injection model, is proposed and it is termed as sparse representation with details injection pansharpening (SRDIP). Unlike the existing sparse representation based methods [17–21], the SRDIP applies the ARSIS concept [9] instead of the compressive sensing reconstruction. In SRDIP, the sparse representation based image decomposition is used to extract the spatial details from the PAN image. Meanwhile, the used dictionaries are learned from the PAN image in the à trous wavelet domain. It improves the applicability of sparse representation based methods since the high resolution MS image is not required for dictionary learning. The idea of learning dictionaries from the PAN image in the wavelet domain has also been applied in [23]. Compared with the method in [23], the proposed method has the following novelties. First, instead of the reconstruction problem, the proposed method adopts the details injection that is accommodated within the ARSIS concept. Second, the role of the learned dictionary in [23] is to ensure the sparsity of high resolution MS image for reconstruction, while the proposed method employs the learned dictionary to extract the spatial details from PAN image. The distinctive usage of learned dictionary in wavelet domain indicates the novelties of proposed method.

This paper is organized as follows. Section 2 briefly reviews the sparse representation theory. The proposed sparse representation based pansharpening with details injection is presented in Section 3. The experimental results and comparisons are given in Section 4. Finally, Section 5 concludes this paper.

2. Sparse representation

The basic idea of sparse representation is that any input signal $\boldsymbol{x} \in \mathbb{R}^n$ can be represented as a linear combination over a dictionary $\mathbf{D} \in \mathbb{R}^{n \times m}$, i.e., $\boldsymbol{x} = \mathbf{D}\boldsymbol{\alpha}$, where $\boldsymbol{\alpha} \in \mathbb{R}^m$ is the sparse coefficient vector with a few non-zero entries. Each column $\boldsymbol{d}_i \in \mathbb{R}^n$ $(i = 1, 2, \ldots, m)$ in the dictionary $\mathbf{D}$ is called an atom. The sparse coefficient vector $\boldsymbol{\alpha}$ can be computed by the following optimization problem:

$$\min_{\boldsymbol{\alpha}} \|\boldsymbol{\alpha}\|_0 \quad \text{subject to} \quad \|\boldsymbol{x} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 \le \varepsilon \tag{1}$$

where the notation $\|\cdot\|_0$ is the ℓ_0-norm counting the number of non-zeros entries in a vector, and $\varepsilon \ge 0$ is the error tolerance of sparse approximation.

Generally, problem (1) is NP-hard and thus it cannot be solved directly. Some approximation solutions have been studied. The orthogonal matching pursuit (OMP) algorithm is a simple and effective one [24]. The OMP is an iterative algorithm which updates the sparse solution by sequentially selecting the most relevant atom. Another well-known approach is the relaxation strategy, which employs the continuous objective functions instead of the ℓ_0-norm function, such as the basis pursuit (BP) algorithm [25] and the non-convex algorithms [26,27].

The OMP, BP and the non-convex algorithms can find the sparse solution under the condition that the sought solution must be sufficiently sparse. The sparsity level is closely related to the dictionary. Thus, the choice of dictionary is the fundamental issue in sparse representation. In the past decade, various methods have been developed to construct the dictionary, which can be divided into two categories: the analytic approach and the learning based approach. In the analytic approach, the dictionary composes of the analytic functions, such as the discrete cosine

Please cite this article as: H. Yin, Sparse representation based pansharpening with details injection model, Signal Processing (2014), http://dx.doi.org/10.1016/j.sigpro.2014.12.017