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Case study

A remote sensing image fusion method based on feedback sparse component analysis

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ABSTRACT

We propose a new remote sensing image (RSI) fusion technique based on sparse blind source separation theory. Our method employs feedback sparse component analysis (FSCA), which can extract the original image in a step-by-step manner and is robust against noise. For RSIs from the China–Brazil Earth Resources Satellite, FSCA can separate useful surface feature information from redundant information and noise. The FSCA algorithm is therefore used to develop two RSI fusion schemes: one focuses on fusing high-resolution and multi-spectral images, while the other fuses synthetic aperture radar bands. The experimental results show that the proposed method can preserve spectral and spatial details of the source images. For certain evaluation indexes, our method performs better than classical fusion methods.

1. Introduction

Remote sensing images (RSIs) with high spectral and spatial resolutions are essential for the complete and accurate description of observed scenes. Remote sensing image (RSI) fusion, also called pansharpening in some field (Alparone et al., 2007), is an effective technique for integrating the spectral and spatial information from panchromatic (PAN) and multi-spectral (MS) images (Wald, 1999). A number of publications have considered the fusion of high-resolution PAN images with lower-resolution MS data to obtain high-resolution MS images (for example, the intensity hue saturation (IHS) (Choi, 2006) color transformation, principle component analysis (PCA) (Gonzalez-Audicana et al., 2004), independent component analysis (ICA) (Chen et al., 2011), multi-scale transform methods (Pajares and Cruz, 2004; Dong et al., 2013; Petrovic and Xydeas, 2004), and their combinations (Wang et al., 2008; González-Audícana et al., 2004; Yu et al., 2012; Shah and Younan, 2008)). Although these methods have removed some redundant information and obtained certain fusion results, there are still disadvantages to each method. IHS transformation and PCA retain spectral distortion, while ICA must satisfy rigorous independent and non-Gaussian constraints. In multi-scale transform fusion algorithms, high-frequency detail information from a PAN image and spectral information from MS images are fused to produce high spatial resolution and rich spectral information. However, in high-frequency regions, there are noise components in the surface details, even though the PAN image has undergone denoising. This is equivalent to fusing components of excessively high frequency. There is thus the potential to improve the spectral fidelity and spatial resolution of RSI fusion.

Sparse representation (SR) is a powerful signal description tool derived from the mechanism of human vision (Olshausen and Field, 1996). Recently, SR has attracted growing interest and has been applied in many image processing areas, such as image denoising (Elad and Aharon, 2006) and image super-resolution (Yang et al., 2010). Furthermore, SR has come to the attention of scholars in the field of RSI fusion (Zhu and Bamler, 2013; Li et al., 2013; Pan et al., 2013). The super-resolution capability and robustness of sparse reconstruction techniques mean that these methods can be expected to give higher spatial resolutions with less spectral distortion than current methods. However, SR methods often need a large dictionary (fixed or learned) and optimization algorithm, leading to expensive computation.

Some fusion algorithms based on blind source separation (BSS) theory have attained satisfactory performance levels (Chen et al., 2011; Wang et al., 2008; Yu et al., 2012). Sparse component analysis (SCA) is a promising BSS algorithm based on SR theory, and is very popular in the signal processing field. In previous research, we proposed a sparse blind image separation algorithm, called the feedback SCA (FSCA) algorithm (Yu et al., 2013; Xu et al., 2013). FSCA can extract sparse components and neglect noise components, making it useful for the fusion process. Therefore, in this

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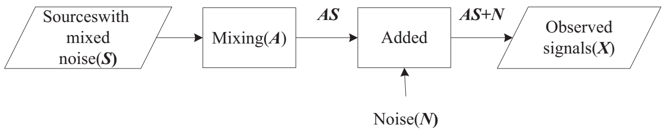

Fig. 1. Mixing model of SCA.

paper, we start from the idea of sparse BSS, extract the sparse components of RSI using FSCA, and then fuse the components via certain rules.

2. Sparse BSS algorithm–FSCA algorithm

2.1. BSS model based on SCA

The problem of sparse BSS is illustrated by the model of SCA in Fig. 1.

The SCA model can be written as a linear matrix model in the form

$$\boldsymbol{X} = \boldsymbol{AS} + \boldsymbol{N};\quad \boldsymbol{X} \in \mathbb{R}^{m\times T};\quad \boldsymbol{A} \in \mathbb{R}^{m\times n};\quad \boldsymbol{S} \in \mathbb{R}^{n\times T} \tag{1}$$

where $\boldsymbol{X}$ are the observations (observed signal matrix), $\boldsymbol{A}$ is the mixing matrix (mixing character of channels), $\boldsymbol{S}$ is the unknown signal (matrix of source signals) to recover, and $\boldsymbol{N}$ is the additive noise matrix. m denotes the number of observations, n denotes the number of sources, and T denotes the number of samples (pixels).

The SCA approach uses the sparsity of sources to solve the BSS problem. The sparsity of source signals implies that each column of $\boldsymbol{S}$ contains just a few significant values (active sources), while most of the elements are almost zero (inactive sources). The goal of SCA is then to estimate $\boldsymbol{A}$ and $\boldsymbol{S}$ as accurately as possible, using only $\boldsymbol{X}$ and the sparsity assumption (Yu et al., 2013).

In the model of SCA, most researchers considered the additive noise. However, there are other sources of noise participating in the mixing system. We refer to such noise as mixing noise, and it has been demonstrated that SCA cannot directly separate the sources in the presence of mixing noise (Yu et al., 2013). We thus propose a new sparse BSS algorithm called the FSCA algorithm to solve the mixing noise problem.

2.2. Anti-mixing-noise sparse BSS algorithm–FSCA algorithm

In the separation process, SCA cannot directly separate all the sources from the mixing noise (Yu et al., 2013), but it always separates one channel well—this is a surprising result. Therefore, if we remove this source channel, then the remaining mixture has one fewer channels, and by repeating the above process, all sources can be effectively separated.

In previous papers (Yu et al., 2013; Xu et al., 2013), we proposed the FSCA algorithm for the above problem (of the mixing noise). The "perfect" separated channel has the minimum mixing element of all of the separated channels, i.e. it has smaller correlation with the original mixtures than the other channels. We thus use normalized correlation coefficient (NCC) to select the "perfect" separated channel. The NCC is calculated as

$$NCC = \frac{\sum_{i,j} |v(i,j) - \bar{v}| \times |v'(i,j) - \bar{v}'|}{\sqrt{\sum_{i,j} |v(i,j) - \bar{v}|^2}\sqrt{\sum_{i,j} |v'(i,j) - \bar{v}'|^2}} \tag{2}$$

where (i, j) denote the position of the pixel. $v(i, j)$ and $v'(i, j)$ are grayscale values of two images. $\bar{v}$ and $\bar{v}'$ are the corresponding mean pixel values.

A flowchart of FSCA is shown in Fig. 2. First, we output the "perfect" source channel with $\boldsymbol{S}'$, and then set this to zero and feed it back into the system as $\boldsymbol{A}_{SCA}\boldsymbol{S}'$ to get the new mixture. Second, we apply SCA to the new mixture. Repeating the above process until only the noise is left, we can extract all images.

2.3. Separation test for MS RSIs

Different RSI bands are the responses to electromagnetic waves incident on the same area, and there are many mixed pixels in low-resolution RSIs. Therefore, multi-band RSIs (MS images) can be thought of as observed mixtures. Remote sensing imagery may suffer interference, such as atmospheric scattering noise and instrument noise, and this noise may be additive or multiplicative. Thus, to test the feasibility of FSCA for real mixing images with noise, we conduct a separation experiment using an RSI taken by the China–Brazil Earth Resources Satellite (CBERS) (512×512 pixels; Doumen, ZhuHai, China). We use SCA and FSCA to separate B4 (0.77–0.89 μm), B2 (0.52–0.59 μm), and B1 (0.45–0.52 μm). The results are shown in Fig. 3.

In Fig. 3, the benefit of SCA and FSCA is seen in the removal of a certain redundancy between MS bands; this is to say, SCA and FSCA are able to decorrelate signals since the separated results of SCA and FSCA are more different from each other than the original bands. FSCA extracts more feature information than SCA, and represents texture features better. For instance, the mountain in the third panel of Fig. 3(c) is better (clearer) than that in the second panel of Fig. 3(b). The content remaining after FSCA can be seen as noise, though it contains some surface information, as seen in Fig. 3(c).

3. RSI fusion method based on FSCA

Considering the different characteristics of RSIs, we propose two fusion schemes for high-resolution MS images and synthetic aperture radar (SAR) bands. First, the fusion rules are introduced.

3.1. Fusion rules

The proposed method uses the following three fusion rules. Consider the fusion of two images, and suppose they have been transformed (separated) by a certain function. We have the prepared fusion components $\boldsymbol{s}_1$ and $\boldsymbol{s}_2$, which are fused according to

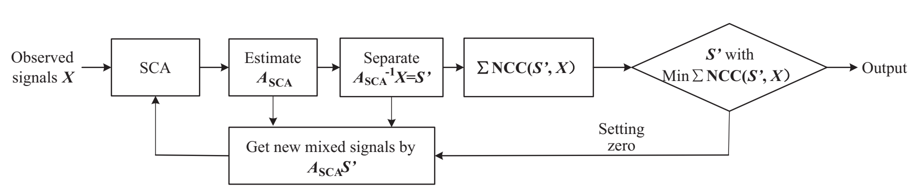

Fig. 2. Flow chart of FSCA.