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Adaptive non-local Euclidean medians sparse unmixing for hyperspectral imagery

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ABSTRACT

Sparse unmixing models based on sparse representation theory and a sparse regression model have been successfully applied to hyperspectral remote sensing image unmixing. To better utilize the abundant spatial information and improve the unmixing accuracy, spatial sparse unmixing methods such as the non-local sparse unmixing (NLSU) approach have been proposed. Although the NLSU method utilizes non-local spatial information as the spatial regularization term and obtains a satisfactory unmixing accuracy, the final abundances are affected by the non-local neighborhoods and drift away from the true abundance values when the observed hyperspectral images have high noise levels. Furthermore, NLSU contains two regularization parameters which need to be appropriately set in real applications, which is a difficult task and often has a high computational cost. To solve these problems, an adaptive non-local Euclidean medians sparse unmixing (ANLEMSU) method is proposed to improve NLSU by replacing the non-local means total variation spatial consideration with the non-local Euclidean medians filtering approach. In addition, ANLEMSU utilizes a joint maximum a posteriori (JMAP) strategy to acquire the relationships between the regularization parameters and the estimated abundances, and achieves the fractional abundances adaptively, without the need to set the two regularization parameters manually. The experimental results using both simulated data and real hyperspectral images indicate that ANLEMSU outperforms the previous sparse unmixing algorithms and, hence, provides an effective option for the unmixing of hyperspectral remote sensing imagery.

1. Introduction

Spectral unmixing was first proposed to cope with the problem of mixed pixels encountered in remote sensing imagery (Demarchi et al., 2012; Tits et al., 2012) and to identify the components of the mixed spectra (also called endmembers) in each pixel, together with their proportions (known as abundances) (Bioucas-Dias et al., 2012, 2013; Keshava and Mustard, 2002; Ma et al., 2014; Tong et al., 2014; Li et al., 2014). Due to the computational tractability and flexibility of the linear mixture model (LMM) (Pu et al., 2014), the LMM has been widely studied. All the unmixing models discussed in this paper are based on the LMM. The conventional spectral unmixing techniques usually consist of an endmember identification step (Zhong et al., 2014b) and an abundance inversion process (Qu et al., 2014). However, the identification of the endmembers is a challenging task because of the lack of prior knowledge about the endmember signatures (Ma et al., 2014).

Sparse unmixing is a novel spectral unmixing technique that is also known as the dictionary-based semi-blind hyperspectral unmixing approach, and it has been widely studied (Iordache, 2011; Iordache et al., 2011, 2012, 2014a,b; Wu et al., 2011; Zhao et al., 2013; Zhong et al., 2014a; Liu and Zhang, 2014; Zhu et al., 2014; Tang et al., 2014). Sparse unmixing assumes that the observed hyperspectral remote sensing imagery can be expressed in a linear sparse regression (Plaza et al., 2011). Unmixing via sparse representation can be reformulated as finding the best combination of endmembers in a prior large standard spectral library, and the sparsity constraint is imposed on the corresponding endmembers' fractional abundances, since the number of endmembers in each mixed pixel is sparse in reality (Iordache et al., 2011). To solve this linear sparse spectral unmixing problem, the sparse unmixing via variable splitting and augmented Lagrangian (SUnSAL) algorithm (Iordache et al., 2011) was proposed. The application of a spectral library in the SUnSAL algorithm successfully circumvents the determination of the endmembers, and better

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results are achieved than with the traditional linear spectral unmixing methods such as non-negative constrained least squares (Iordache, 2011; Iordache et al., 2011).

As the research into sparse unmixing has progressed, the spatial information existing in the remote sensing imagery has also been utilized, and several spatial sparse unmixing algorithms have been developed, such as sparse unmixing via variable splitting augmented Lagrangian and total variation (SUnSAL-TV) (Iordache et al., 2012) and non-local sparse unmixing (NLSU) (Zhong et al., 2014a). Compared with SUnSAL-TV, which utilizes the spatial information in a first-order pixel neighborhood system, NLSU has been proved to be an efficient and powerful spatial sparse unmixing algorithm that considers the non-local spatial information of the whole abundance image. In the NLSU algorithm, each mixed pixel's abundance is reformulated with the non-local means (NLM) (Buades et al., 2005a,b) total variational method as the spatial consideration, using a weighted averaging of a group of non-local pixels' abundances, and the Euclidean distance is utilized to measure the similarity of each neighborhood. However, due to the existence of the inaccurate estimated unmixing abundances, the weights measured by the Euclidean distance will not be exact. Unfortunately, the performance of NLSU largely depends on the reliability of the weights, and it is inevitable that weights computed from estimated fractional abundances will lead to an inaccurate spatial relationship. That is to say, the outliers in the weights, together with the corresponding unreliable similar windows, should be excluded in the process of computing the fractional abundances for the current pixel. Moreover, the two regularization parameters in the NLSU model, one before the sparsity regularization term, and the other connected with the spatial constraint for the contribution of the spatial regularization term, need to be determined in real applications, which is a difficult task and is quite time-consuming.

To obtain a more reliable spatial correlation and to obtain the regularization parameters of the model adaptively, an adaptive non-local Euclidean medians sparse unmixing (ANLEMSU) method is proposed. ANLEMSU improves NLSU by replacing the NLM total variation spatial consideration by the non-local Euclidean medians filtering approach, and it utilizes a joint maximum a posteriori (JMAP) (Mohammad-Djafari, 1996; Hsiao et al., 2002) strategy to acquire the relationships between the regularization parameters and the estimated fractional abundances.

The contributions of this paper are twofold:

(1) An efficient spatial consideration term that can cope with high-level noise, non-local Euclidean medians, is applied. This improves the traditional NLM method by reversing the top 50% of the weight values and abandoning the rest after sorting them in decreasing order and then computing the Euclidean medians with iteratively reweighted least squares (IRLS).
(2) The regularization parameters are obtained adaptively, based on a JMAP strategy. In the ANLEMSU model, there are several unknown values: the objective fractional abundances and the two regularization parameters. To jointly estimate the unknowns is an ideal strategy. The ANLEMSU approach utilizes the relationships of the prior probability distributions between the abundances and the regularization parameters deduced from JMAP, and it estimates the regularization parameters and the unknown fractional abundances by an alternating iterative process.

The rest of this paper is organized as follows. In Section 2, NLSU is reviewed. The ANLEMSU method is then proposed in Section 3, based on the techniques of non-local Euclidean medians (NLEM) and JMAP. Section 4 presents the experiments and analyses with two simulated datasets and two real hyperspectral remote sensing images. Section 5 discusses the sensitivity of ANLEMSU in relation to the different parameters. Finally, the conclusions are drawn in Section 6.

2. Non-local sparse unmixing

2.1. Sparse unmixing

In hyperspectral remote sensing imagery, each mixed pixel is represented as a vector $\mathbf{y}$ with L dimensions, and L is the number of spectral bands. Due to the computational tractability and flexibility, the LMM has been widely used in many applications, and the unmixing models discussed in this paper are all based on the LMM, shown as (1).

$$\mathbf{y} = \mathbf{M}\boldsymbol{\alpha} + \mathbf{n} \tag{1}$$

where $\mathbf{M}$ is a $L \times q$ matrix containing q spectral signatures (called endmembers), and $\boldsymbol{\alpha}$ is a q-dimensional vector containing the corresponding abundance of the endmember in $\mathbf{M}$. $\mathbf{n}$ denotes the noise and model error and is also an $L \times 1$ vector. Because the components of $\boldsymbol{\alpha}$ represent the fractional abundances, they should satisfy the abundance non-negative constraint (ANC) and abundance sum-to-one constraint (ASC) (Heinz and Chang, 2001), as follows:

$$\alpha_i \geqslant 0 \ (i = 1, 2, \ldots, q) \tag{2}$$

$$\sum_{i=1}^{q} \alpha_i = 1 \tag{3}$$

Sparse unmixing adopts another direction, which circumvents the determination of endmembers by selecting the optimal sparse combination of endmembers from a potentially quite large standard spectral library known in advance. Based on the LMM and the known spectral library, the sparse unmixing model is written as:

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{n} \tag{4}$$

where $\mathbf{A}$ acts as the large spectral library with a size of $L \times m$, and $\mathbf{x}$ represents the m-dimensional vector as the abundance corresponding to library $\mathbf{A}$, and is sparse. Similarly, the two constraints for the abundances should also be considered in the sparse unmixing model as:

$$\min_{\mathbf{x}} \|\mathbf{x}\|_0 \ s.t.\ \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2 \leqslant \delta, \quad \mathbf{x} \geqslant \mathbf{0}, \quad \mathbf{1}^T\mathbf{x} = 1 \tag{5}$$

where $||\mathbf{x}||_0$ represents the number of non-zero components in vector $\mathbf{x}$, and $\delta \geqslant 0$ is the noise or model error. $\mathbf{x} \geqslant \mathbf{0}$ and $\mathbf{1}^T\mathbf{x} = 1$ denote the ANC and ASC, respectively. However, since the l_0 term in (5) is a typical NP-hard problem, it can be relaxed as the l_1 norm to obtain the sparsest solution under certain conditions (Candès and Romberg, 2007). Therefore, (5) can be replaced as follows:

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \ s.t.\ \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2 \leqslant \delta, \quad \mathbf{x} \geqslant \mathbf{0}, \quad \mathbf{1}^T\mathbf{x} = 1 \tag{6}$$

where $\|\mathbf{x}\|_1 = \sum_{i=1}^{m} |\mathbf{x}_i|$, and $\mathbf{x}_i$ represents the ith abundance in vector $\mathbf{x}$. To tackle this convex optimization problem, SUnSAL was proposed. However, classical sparse unmixing focuses on analyzing the hyperspectral data without considering the spatial correlations.

2.2. Non-local sparse unmixing

With the ongoing research into sparse unmixing techniques, the spatial information is now treated as important prior knowledge that can be incorporated into the conventional sparse unmixing model. NLSU was proposed based on an NLM method, combining the non-local spatial information (Manjón et al., 2008; Protter et al., 2009; Qian and Ye, 2013) and making systematic use of all possible self-predictions of the abundance maps. Zhong et al.