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A Poisson nonnegative matrix factorization method with parameter subspace clustering constraint for endmember extraction in hyperspectral imagery

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ABSTRACT

A new Bayesian method named Poisson Nonnegative Matrix Factorization with Parameter Subspace Clustering Constraint (PNMF-PSCC) has been presented to extract endmembers from Hyperspectral Imagery (HSI). First, the method integrates the liner spectral mixture model with the Bayesian framework and it formulates endmember extraction into a Bayesian inference problem. Second, the Parameter Subspace Clustering Constraint (PSCC) is incorporated into the statistical program to consider the clustering of all pixels in the parameter subspace. The PSCC could enlarge differences among ground objects and helps finding endmembers with smaller spectrum divergences. Meanwhile, the PNMF-PSCC method utilizes the Poisson distribution as the prior knowledge of spectral signals to better explain the quantum nature of light in imaging spectrometer. Third, the optimization problem of PNMF-PSCC is formulated into maximizing the joint density via the Maximum A Posterior (MAP) estimator. The program is finally solved by iteratively optimizing two sub-problems via the Alternating Direction Method of Multipliers (ADMM) framework and the FurthestSum initialization scheme. Five state-of-the art methods are implemented to make comparisons with the performance of PNMF-PSCC on both the synthetic and real HSI datasets. Experimental results show that the PNMF-PSCC outperforms all the five methods in Spectral Angle Distance (SAD) and Root-Mean-Square-Error (RMSE), and especially it could identify good endmembers for ground objects with smaller spectrum divergences.

1. Introduction

Since the birth of imaging spectrometer, the research on HSI is being a hot topic in the remote sensing community (Bioucas-Dias et al., 2013; Thenkabail et al., 2016; Tong et al., 2014). Hyperspectral imaging collects hundreds of narrow spectral bands of ground objects, and it has enormous potentials in identifying and recognizing subtle differences among ground objects on the earth surface (Tong et al., 2014). However, because of limited spatial resolutions of imaging spectrometer and homogenous mixture of distinct materials, the observed spectral reflectance at each pixel is physically a spectral mixture of several pure materials (i.e., endmembers) (Bioucas-Dias and Plaza, 2011; Shi and Wang, 2014). The spectral mixture problem in HSI adversely hinders its realistic applications including land cover mapping (Clark and Kilham, 2016; Meyer and Okin, 2015), coastal wetland monitoring (Liu et al., 2016; Manzo et al., 2015), precision agriculture (Landmann et al., 2015; Malec et al., 2015) and so on. Therefore, spectral unmixing is urgent to qualify the fractions or proportions of each endmember (i.e., abundance) present in the mixed pixels (Bioucas-Dias et al., 2012; Wang et al., 2015; Zhong et al., 2016).

Endmember extraction is a preliminary but key work for operating spectral unmixing on the HSI data (Veganzones and Grana, 2008; Xu et al., 2014). Proper endmembers directly impact the estimated abundance at each pixel and greatly benefit the result of spectral unmixing. The obtainment of endmember signatures can be classified into two aspects (Bioucas-Dias and Plaza, 2011; Bioucas-Dias et al., 2012): (1) the reference-endmembers are measured on the ground or in the library using a field spectroradiometer, and (2) the image-endmembers are estimated from

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hyperspectral images using certain endmember extraction methods. Complicated work in spectral calibration is necessarily requiring for spectral matching between reference-endmembers and image pixels, because of their different collection conditions (e.g., imaging sensors, atmospheric effects and scattering conditions) (Stagakis et al., 2016; Zare and Ho, 2014). In contrast, the problem does not exist in image-endmembers, and the simpler procedure brings them more popularity in spectral unmixing (Somers et al., 2012; Xu et al., 2014).

Many extraction algorithms for image-endmembers have been presented in current literatures and they can be grouped into two schemes: (1) pure-pixel scheme and (2) nonpure-pixel scheme. The pure-pixel scheme regards that at least one endmember exists in the image scene. It expects the volume of the inflating simplex composed by the HSI data to be as large as possible and then finds vertices of the convex simplex. The benchmark method of Pixel Purity Index (PPI) iteratively projects each spectral data into random vectors and selects the purest endmembers by sorting account records of extreme pixels (Chang and Plaza, 2006). N-FINDER selects endmember signatures by looking for a simplex formed by the given data and owning the largest volume (Winter, 1999). The Vertex Component Analysis (VCA) determines endmembers from the extreme of the projection that has the direction orthogonal to the subspace spanned by the identified endmember signatures at each iteration (Nascimento and Dias, 2005). More recent representative pure-pixel based algorithms include the collaborative sparse regression algorithm (Iordache et al., 2014), rank-two nonnegative matrix factorization method (Gillis et al., 2015), and weighted fuzzy purified-means clustering method (Xu et al., 2016).

Nonpure-pixel scheme assumes that the image scene does not contain any pure pixels (i.e., endmembers). In this manuscript, we focus our topic in nonpure-pixel scheme because it seeks "virtual" endmembers that are closely associated with physically meaningful spectral signatures of true materials (Geng et al., 2013; Zhong et al., 2016). Typical nonpure-pixel methods include geometrical methods, matrix factorization methods and statistical methods. Representative examples of geometrical methods are Iterative Constrained Endmembers (ICE) (Berman et al., 2004), convex analysis-based Minimum Volume Enclosing Simplex (MVES) (Chan et al., 2009) and Minimum Volume Simplex Analysis (MVSA) (Li et al., 2015). The matrix factorization methods simultaneously decompose the HSI data into an endmember matrix and its corresponding abundance matrix. Typical methods include Sparse Nonnegative Matrix Underapproximation (SNMU) (Gillis and Plemmons, 2013), Multilayer Nonnegative Matrix Factorization (MLNMF) (Rajabi and Ghassemian, 2015), Robust Nonnegative Matrix Factorization (RNMF) (Févotte and Dobigeon, 2015), Geometric Nonnegative Matrix Factorization (GNMF) (Yang et al., 2015) and Constrained Nonnegative Matrix Factorization (CNMF) (Du et al., 2016). The statistical methods formulate endmember extraction into a statistical inference problem and aim for highly mixed hyperspectral image scenarios, with examples of Independent Component Analysis (ICA) (Wang et al., 2015) and Bayesian approaches such as normal endmember spectral unmixing (Zhuang et al., 2015) and the hierarchical Bayesian algorithm (Altmann et al., 2015). Unfortunately, all the current methods have their own drawbacks and disadvantages. For example, the MVSA stands on the famous Craig-criterion, and it states that the vertices of the minimum-volume simplex enclosing the HSI pixels will yield high fidelity estimates of endmember signatures associated with the HSI data. However, the noisy observations might bring about bad proximity of extracted endmembers to true endmember signatures (Lin et al., 2015). The convergence of CNMF highly correlates with the initialization of endmembers (Sun et al., 2016). Moreover, the matrix factorization methods could not provide clear geometrical or physical explanations for extracted endmembers (Mørup and Hansen, 2012). The assumption of ICA that abundance fractions come from mutually independent sources might contradict with the case of HSI data and it accordingly could not guarantee good estimations of endmembers (Bioucas-Dias et al., 2012; Wang et al., 2015). The Bayesian approaches implement the Gaussian or other distribution as priors of HSI data and that could not carefully consider the quantum nature of light in imaging spectrometer (Zou and Xia, 2016). Besides, the statistical nature of Bayesian approaches renders that they could not provide clear geometrical or physical meanings of the endmembers. Therefore, there is still a lot of rooms to explore endmembers from the nonpure-pixel assumption.

In this manuscript, under the nonpure-pixel assumption in the image scene, we propose a new Bayesian approach termed as PNMF-PSCC to explore the endmember extraction problem. Our motivation is to promote the Bayesian nonnegative matrix fraction method with the Poisson prior distribution and the PSCC, and apply the new method into the problem of endmember extraction of the HSI data. The method considers the subspace clustering of all pixels in the parameter space rather than the spectrum space of HSI data and implements the PSCC into the statistical program. It also adopts the Poisson distribution as priors of spectrum signals in HSI data to show the quantum nature of light in imaging spectrometer. Compared with other methods, the contributions of PNMF-PSCC method are in the following:

(1) The PNMF-PSCC assumes the Poisson prior distribution of spectrum signal of HSI data and formulates the blind spectral unmixing of nonnegative matrix factorization into a Bayesian inference problem. It stands on the Bayesian framework and clearly differs from current geometrical methods and matrix factorization methods. The Poisson prior distribution of HSI data in PNMF-PSCC shows the quantum nature of light in imaging spectrometer and it is different from those of statistical methods including ICA and Bayesian approaches.
(2) The method integrates the PSCC of HSI data into the Bayesian framework and provides extracted endmembers with clear geometrical meanings. The PSCC assumes the endmembers can be linearly represented by all the other pixels in the parameter subspace and constructs a convex hull in the parameter space. Estimating endmembers can then be explained as finding archetypes of convex hull in the parameter space.
(3) The solution of PNMF-PSCC is optimized by iteratively minimizing two nonlinear sub-problems via the ADMM framework. The FurthestSum initialization scheme (Mørup and Hansen, 2012) is also utilized to speed up the convergence of ADMM and meanwhile to avoid selecting too-close pixels as endmembers. No much complicated parameters involved render that the method is easily to implement in realistic applications of spectral unmixing.

The rest of our manuscript is arranged as follows. Section 2 presents relevant background of our PNMF-PSCC method. Section 3 describes the PNMF-PSCC method for endmember extraction. Section 4 lists and discusses experimental results on synthetic and real hyperspectral images for extracting endmembers. Section 5 states conclusions and future work of our manuscript.

2. Relevant background

In this section, relevant knowledge will be briefly reviewed. Section 2.1 reviews the linear spectral mixture model of HSI data