

Accepted Manuscript

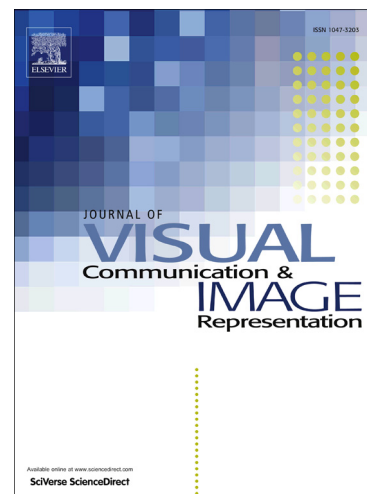
Regularized MSBL Algorithm with Spatial Correlation for Sparse Hyperspectral Unmixing

Fanqiang Kong, Yunsong Li, Wenjun Guo

PII: S1047-3203(16)30145-6
DOI: <http://dx.doi.org/10.1016/j.jvcir.2016.07.019>
Reference: YJVC I 1823

To appear in: *J. Vis. Commun. Image R.*

Received Date: 15 June 2016
Revised Date: 16 July 2016
Accepted Date: 23 July 2016



Please cite this article as: F. Kong, Y. Li, W. Guo, Regularized MSBL Algorithm with Spatial Correlation for Sparse Hyperspectral Unmixing, *J. Vis. Commun. Image R.* (2016), doi: <http://dx.doi.org/10.1016/j.jvcir.2016.07.019>

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Regularized MSBL Algorithm with Spatial Correlation for Sparse Hyperspectral Unmixing

Fanqiang Kong, Yunsong Li, Wenjun Guo

Abstract: Sparse unmixing is a promising approach that is formulated as a linear regression problem by assuming that observed signatures can be expressed as a linear combination of a few endmembers in the spectral library. Under this formulation, a novel regularized multiple sparse Bayesian learning model, which is constructed via Bayesian inference with the conditional posterior distributions of model parameters under a hierarchical Bayesian model, is proposed to solve the sparse unmixing problem. Then, the total variation regularization and the non-negativity constraint are incorporated into the model, thus exploiting the spatial information and the physical property in hyperspectral images. The optimal problem of the model is decomposed into several simpler iterative optimization problems that are solved via the alternating direction method of multipliers, and the model parameters are updated adaptively from the algorithm. Experimental results on both synthetic and real hyperspectral data demonstrate that the proposed method outperforms the other algorithms.

Key words: hyperspectral unmixing, sparse Bayesian learning, total variation, multiple measurement vectors model

1. Introduction

Hyperspectral imagery has a wide range of applications in environmental monitoring, target detection and resource surveys [1]-[4]. Due to the insufficient spatial resolution of hyperspectral remote sensors, mixed pixels are always encountered in remote sensing imagery. To address this problem, the hyperspectral unmixing technique, which is used to decompose each pixel's spectrum to identify the pure constituent spectra (endmembers) and estimate the abundances of the endmembers in the mixed pixel, has recently been proposed [4], [5]. There are two basic hyperspectral unmixing models that we use to analyze the mixed pixel problem: the linear mixture model (LMM) and the nonlinear mixture model (NLMM). Owing to the flexibility and tractability, the linear mixture model is widely used for the hyperspectral unmixing problem. The traditional linear unmixing methods for solving the unmixing problem can be divided into two steps: (a) endmember extraction and (b) abundances estimation. We can list some popular endmember extraction algorithms, such as the hybrid endmember extraction algorithm [6], orthogonal subspace projection [7], pixel purity index (PPI) [8], N-FINDR algorithm [9] and vertex component analysis (VCA) method [10]. However, some of these methods [7]-[10] assume that the hyperspectral data contains at least one pure pixel per endmember. If the pure pixel assumption is not fulfilled, these methods are very likely to fail.

Sparse unmixing, as a semi-supervised unmixing method, which assumes that the mixed pixels of a hyperspectral image can be expressed as a linear combination of spectral signatures from a spectral library that is known in advance [5], has been proposed to overcome this problem. Due to the number of signatures in the spectral library being much larger than the number of actual endmembers present in a hyperspectral image, the hyperspectral unmixing problem can be represented as a semi-supervised sparse signal regression problem. Thus, sparse regression techniques can be used [5], [11] to solve it.

Several sparse regression techniques, such as convex relaxation algorithms [12]-[14], greedy algorithms (GAs)

F. Kong and W. Guo are with the College of Astronautics, Nanjing University of Aeronautics and Astronautics, Nanjing, 210016, China (e-mail: kongfq@nuaa.edu.cn, nuaaguowenjun@126.com).

Y. Li is with the State Key Laboratory of Integrated Service Networks, Xidian University, Xi'an 710071, China (e-mail: ysl@mail.xidian.edu.cn).

Download English Version:

<https://daneshyari.com/en/article/6938454>

Download Persian Version:

<https://daneshyari.com/article/6938454>

[Daneshyari.com](https://daneshyari.com)