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Bayesian dictionary learning for hyperspectral image super resolution in mixed Poisson–Gaussian noise☆

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ABSTRACT

This paper develops a Bayesian dictionary learning method for hyperspectral image super resolution in the presence of mixed Poisson–Gaussian noise. A likelihood function is first designed to deal with the mixed Poisson–Gaussian noise. A fusion optimization model is then introduced, including the data-fidelity term capturing the statistics of mixed Poisson–Gaussian noise, and a beta process analysis-based sparse representation regularization term. In order to implement the proposed method, we use alternating direction method of multipliers (ADMM) for simultaneous Bayesian nonparametric dictionary learning and image estimation. Compared with conventional dictionary learning methods, the introduced dictionary learning method is based on a popular beta process factor analysis (BPFA) for an adaptive learning performance. Simulation results illustrate that the proposed method has a better performance than several well-known methods in terms of quality indices and reconstruction visual effects.

1. Introduction

Hyperspectral (HS) image has various applications, such as resource management, remote sensing and monitoring, and so on [1]. Because of various limitations from spectral imaging techniques, the received HS image is generally low spacial resolution and corrupted by various noise [2]. Therefore, it is very important to develop software techniques to enhance the resolution of the acquired HS image.

Although single image super resolution methods have been well developed [3–6], multiband image super resolution study is relatively less and has become a significant topic, recently. Some methods for HS image super resolution have been proposed in the recent years. The first category method, which is based on Bayesian inference is to find the maximization posteriori estimator by combining the likelihood function and the defined appropriate image prior [7–10]. In addition, the method based on spectral unmixing or matrix factorization has been explored to fuse HS and multispectral (MS) images. Yokoya et al. [11] first proposed a coupled nonnegative matrix factorization (CNMF) approach to fuse HS and MS images by factorizing the image into endmember and abundance with line spectral unmixing technique. Several improved approaches by considering nonnegative and sparse constraints on the endmember and abundance matrices were also proposed [12–16]. Simoes et al. [17] proposed a total variation regularization for endmember. Wei et al. [18] first converted the original image to the lower dimensional image subspace, then proposed a method based on sparse representation for HS image super resolution. Without the auxiliary MS image, Zhao et al. [19] proposed a joint regulation of spatial and spectral nonlocal similarities method for HS image super resolution. However, all these methods are based on the specific prior knowledge of the image noise and can only remove Gaussian noise.

In practice, real HS images usually are corrupted by several different types of noise. Except Gaussian noise, Poisson noise is another important noise source in HS image due to the quantum nature of light in the imaging device [20,21]. In recent years, various methods for Poissonian image restoration were proposed in [22–29]. Especially, in HS image processing, Othman et al. [20] proposed derivative-domain wavelet shrinkage method for noise reducing of HS image. Mansouri et al. [21] presented an adaptive method with semi-norm total variation regularization term on spatial and spectral domain to remove Poisson noise of hyperspectral image. Yang et al. [23] proposed a Poisson–Gaussian mixed model for HS image denoising by principal component analysis.

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Ye et al. [24] presented a based on sparse representation method for denoising HSI corrupted by mixed noise. Qian et al. [25] proposed a nonlocal spectral-spatial structured sparse representation for Poisson–Gaussian mixed noise reducing of HS imagery. Bajic et al. [26] presented a single image super resolution method in the case of mixed Poisson–Gaussian noise. However, these introduced methods above cannot be directly used for HS image super resolution in the case of the mixture of Poisson and Gaussian noise. So it is necessary to develop a super resolution method for HS image corrupted by Poisson–Gaussian noise, which is more consisting with real obtained HS image.

In this paper, we propose a Bayesian nonparametric dictionary learning method for HS image super resolution. We first derive a likelihood function to deal with the mixed Poisson–Gaussian noise. To overcome ill-posedness of the problem, we introduce a sparse representation regularization term. The key problem of sparse representation is how to learning the dictionary. Typical dictionary learning approach such as K-SVD requires some predefined parameters such as dictionary size and the sparsity level T to determine how many dictionary elements are used [30]. If these parameters are set unaccurately, the reconstruction result will be degraded greatly. In this paper, Bayesian nonparametric dictionary learning is introduced, which is based on a popular beta process factor analysis (BPFA) [31], which has shown good performance in many application areas [32–36]. The work of Akhtar [35] followed the spectral unmixing method to infer the endmember as the learned dictionary and abundance matrix separately. In [35], the observed HS image is used as the dictionary training data. However, when the observed image is corrupted by the heavy noise, especially, in the case of the mixed Poisson–Gaussian noise, the error of estimated dictionary is big. In contrast, we learn the dictionary in the reduced low dimension subspace by SVD factorization of the observed HS image. This dimensionality reduction has two advantages. One is that it is computationally more efficient to work in a lower dimensional space than in the original space. The other advantage is that, since the number of variables to be estimated is significantly reduced as well as the noise by SVD, the estimated dictionary is normally more accurate. Furthermore, in our model, we combine the dictionary learning and image estimating into a unifying optimization formulation, and update the dictionary self-adaptively by variational Bayesian method according to the estimated image on current iteration, so that the estimated error is reduced. At last, in the paper, we consider the case of mixed Poisson–Gaussian noise which extent the traditional Gaussian noise case and propose a cost function, which contains two data-fidelity terms capturing the statistics of the mixed Poisson–Gaussian noise. Simulation results illustrate that the proposed method has a better performance than several well-known methods both in terms of visual effectiveness and quality indices, and costs less time than Akhtar method [35].

The remainder of this work is organized as follows. Section 2 gives the problem model and estimation method. Section 3 describes Bayesian dictionary learning and optimization algorithm. Experimental results are presented in Section 4. Section 5 gives the conclusion.

2. Problem model and estimation method

2.1. Observation model of HS and MS images

We consider the following degraded observed model of HS and MS images:

$$Y_h = Poisson(YM) + V_h, Y_m = Poisson(RY) + V_m, \tag{1}$$

where $Poisson$ denotes the Poisson distribute, $Y \in \mathbb{R}^{N_h \times n_m}$ denotes the unknown high resolution HS image to estimate, N_h is the number of spectral bands, n_m is the number of pixels of very band, $Y_h \in \mathbb{R}^{N_h \times n_h}$ denotes the observed low resolution HS image, n_h is pixels of every band, $Y_m \in \mathbb{R}^{N_m \times n_m}$ denotes the observed MS image composed of N_m bands, $M \in \mathbb{R}^{n_m \times n_h}$ denotes the known degrade matrix including spatial blurring filter and down sampling matrix, $R \in \mathbb{R}^{N_m \times N_h}$ is the known spectral response, and V_h and V_n denote observed Gaussian noise. Our goal is to estimate Y from the observed images Y_h and Y_m.

2.2. Proposed estimation method

In the subsection, we propose a new estimation method by introducing two data-fidelity terms capturing the statistics of mixed Poisson–Gaussian noise and BPFA-based sparse representation regularization term.

(1) Poisson–Gaussian data-fidelity

Let $\overline{Y}_h, \overline{Y}_m$ denote $Poisson(YM), Poisson(RY)$, respectively, then

$$Y_h = \overline{Y}_h + V_h, Y_m = \overline{Y}_m + V_m, \tag{2}$$

where random vectors $\overline{Y}_h, \overline{Y}_m$ have Poisson distribution, and V_h, V_m have Gaussian distribution. For discussion convenience, let $Y_{h(ij)}$ and $Y_{m(ij)}$ be pixel of the observed HS and MS images at the location ij, respectively. We have the following moment generating functions:

(1) For the Poisson case, $\overline{Y}_{h(ij)} = Poisson((YM)_{(ij)})$, with parameter $(YM)_{(ij)} > 0$, the moment generating function of $\overline{Y}_{h(ij)}, \overline{Y}_{m(ij)}$ is, respectively

$$n\phi_{\overline{Y}_{h(ij)}}(t) = \exp\{(YM)_{(ij)}(e^t - 1)\},$$
$$\phi_{\overline{Y}_{m(ij)}}(t) = \exp\{(RY)_{(ij)}(e^t - 1)\}. \tag{3}$$

(2) For the Gaussian case, $V_{h(ij)} \sim \mathcal{N}(0, \sigma_{V_{h(ij)}}), V_{m(ij)} \sim \mathcal{N}(0, \sigma_{V_{m(ij)}})$, the moment generating function of $V_{h(ij)}, V_{m(ij)}$ is respectively

$$\phi_{V_{h(ij)}}(t) = \exp\{\frac{\sigma_{V_{h(ij)}} t^2}{2}\},$$
$$\phi_{V_{m(ij)}}(t) = \exp\{\frac{\sigma_{V_{m(ij)}} t^2}{2}\}. \tag{4}$$

(3) For the mixture case, $Y_{h(ij)} = \overline{Y}_{h(ij)} + V_{h(ij)}, Y_{m(ij)} = \overline{Y}_{m(ij)} + V_{m(ij)}$, the moment generating function of $Y_{h(ij)}, Y_{m(ij)}$ can be calculated by

$$\phi_{Y_{h(ij)}}(t) = \mathbb{E}[e^{t\left(\overline{Y}_{h(ij)} + V_{h(ij)}\right)}]$$
$$= \exp\{(YM)_{(ij)}(e^t - 1) + \frac{\sigma_{V_{h(ij)}} t^2}{2}\},$$
$$\phi_{Y_{m(ij)}}(t) = E[e^{t\left(\overline{Y}_{m(ij)} + V_{m(ij)}\right)}]$$
$$= \exp\{(RY)_{(ij)}(e^t - 1) + \frac{\sigma_{V_{m(ij)}} t^2}{2}\}, \tag{5}$$

where $\mathbb{E}[\cdot]$ denotes mathematical expectation.

From the properties of the generating function, we know

$$\mathbb{E}[Y_{h(ij)}] = \phi'_{Y_{h(ij)}}(0) = \overline{Y}_{h(ij)} = (YM)_{(ij)},$$
$$\mathbb{E}[Y^2_{h(ij)}] = \phi''_{Y_{h(ij)}}(0) = (YM)^2_{(ij)} + (YM)_{(ij)} + \sigma_{V_{h(ij)}}, \tag{6}$$

and

$$\mathbb{E}[Y_{m(ij)}] = \phi'_{Y_{m(ij)}}(0) = \overline{Y}_{m(ij)} = (RY)_{(ij)},$$
$$\mathbb{E}[Y^2_{m(ij)}] = \phi''_{Y_{h(ij)}}(0) = (RY)^2_{(ij)} + (RY)_{(ij)} + \sigma_{V_{m(ij)}}, \tag{7}$$

where the superscript notation $'$ reflects the derivative operator. The variance of $Y_{h(ij)}, Y_{m(ij)}$ can be calculated as

$$Var[Y_{h(ij)}] = (YM)_{(ij)} + \sigma_{V_{h(ij)}},$$
$$Var[Y_{m(ij)}] = (RY)_{(ij)} + \sigma_{V_{m(ij)}}. \tag{8}$$

Furthermore, we assume that $Y_{h(ij)}, Y_{m(ij)}$ have Gaussian distribution. That is,

$$Y_{h(ij)} \sim \mathcal{N}\left((YM)_{(ij)}, (YM)_{(ij)} + \sigma_{V_{h(ij)}}\right),$$
$$Y_{m(ij)} \sim \mathcal{N}\left((RY)_{(ij)}, (RY)_{(ij)} + \sigma_{V_{m(ij)}}\right). \tag{9}$$

Based on the maximization likelihood (ML) estimation approach, a likelihood object function for high resolution HS image estimation is expressed as

$$\max_Y p(Y_h|YM) \cdot p(Y_m|RY), \tag{10}$$