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HYPERSONTURAL UNMIXING ACCOUNTING FOR SPATIAL CORRELATIONS AND ENDMEMBER VARIABILITY

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ABSTRACT
This paper presents an unsupervised Bayesian algorithm for hyperspectral image unmixing accounting for endmember variability. This variability is obtained by assuming that each pixel is a linear combination of random endmembers weighted by their corresponding abundances. An additive noise is also considered in the proposed model generalizing the normal compositional model. The proposed model is unsupervised since it estimates the abundances and both the mean and the covariance matrix of each endmember. A classification map indicating the class of each pixel is also obtained based on the estimated abundances. Simulations conducted on a real dataset show the potential of the proposed model in terms of unmixing performance for the analysis of hyperspectral images.

Index Terms— Hyperspectral imagery, endmember variability, image classification, Markov chain Monte-Carlo.

1. INTRODUCTION
Unmixing hyperspectral (HS) images consists of decomposing a pixel spectrum into a combination of pure constituent spectra, or endmembers, and a set of corresponding fractions, or abundances. The mixture model associated with spectral unmixing can be linear or nonlinear, depending on the hyperspectral image under consideration [1]. Endmember variability (EV) has been identified as one of the most profound sources of error in abundance estimation [2,3]. Many algorithms have been proposed to mitigate EV effects. These algorithms are often classified into bundle approaches (that consider each physical component in the image). This allows the GNCM to account for EV by considering a Gaussian distribution, whose variances change from one spectral band to another, for each physical component in the image. This allows the GNCM to capture the spectral variations of each physical element with respect to each spectral band. Second, it introduces an additional constraint (i.i.d.) noise $e_n$ as follows

$$y_n = \sum_{r=1}^{R} a_{rn} s_{rn} + e_n = S_n a_n + e_n \quad (1)$$

where $a_n = [a_{1n}, \ldots, a_{Rn}]^T$ is the $(R \times 1)$ abundance vector of the $n$th pixel, $s_{rn} \sim \mathcal{N}(m_r, \text{diag}(\sigma_r^2))$ is the $r$th endmember associated with the $n$th pixel, $S_n = [s_{1n}, \ldots, s_{Rn}]$, $\sigma_r^2 = [\sigma_{1r}^2, \ldots, \sigma_{Sr}^2]^T$ is the variance vector of the $r$th endmember, $M = [m_{1}, \ldots, m_{R}]$ is the $(R \times R)$ matrix containing the endmember means of the image, $e_n \sim \mathcal{N}(0_r, \psi_n I_L)$ is an additive residual Gaussian noise, $\psi_n \in \mathbb{R}$, $0_r$ is an $(L \times 1)$ vector of 0 and $I_L$ is the $(L \times L)$ identity matrix. The abundance vector $a_n$ contains proportions and thus should satisfy the physical positivity and sum-to-one (PSTO) constraints $a_{rn} \geq 0, \forall r \in \{1, \ldots, R\}$ and $\sum_{r=1}^{R} a_{rn} = 1$.

There are several motivations for considering the GNCM. First, model (1) accounts for EV by considering a Gaussian distribution, whose variance $\sigma_r^2$ change from one spectral band to another, for each physical component in the image. This allows the GNCM to capture the spectral variations of each physical element with respect to each spectral band. Second, model (1) generalizes the LMM...
model since the GNCM reduces to the LMM for $\sigma_2^2 = 0$, $\forall r$. Third, model (1) generalizes the NCM since it introduces an additional residual Gaussian noise $e$ that makes the proposed model more robust with respect to mismodeling. Note that the GNCM reduces to the NCM for $\psi_n^2 = 0$, $\forall n$. To summarize, the main motivations for studying model (1) is that it generalizes the standard LMM and NCM and allows EV to be taken into account.

2.2. Likelihood

Using the observation model (1), the Gaussian properties of both the noise sequence $e_n$ and the endmembers, and exploiting independence between the noise samples in different spectral bands, yield the following likelihood

$$f(y_n|A, M, \Sigma, \Psi) \propto \left( \prod_{l=1}^{L} A_{ln} \right) \frac{1}{\sqrt{2\pi}} \int \exp \left\{ -\frac{1}{2} \Psi_{n} \{(y_n - Ma_n) \} \right\}$$

(2)

where $A$ is an $(L \times N)$ matrix whose elements are given by $A_{ln} = \left( \sum_{r=1}^{R} a_{ln}^2 \right)^{1/2}$, $A = [a_1, \cdots, a_N]$ is an $(R \times N)$ abundance matrix, $N$ is the number of pixels, $\Sigma = (\sigma_n^2)_{n=1}^{N}$ is an $(R \times L)$ matrix, $\Psi = [\psi_1, \cdots, \psi_L]$ is an $(1 \times N)$ vector and $\circ$ denotes the Hadamard (termwise) product. Note that the elements of $A$ depend jointly on the noise variances, the endmember variances and the pixel abundances contrary to the LMM.

2.3. Parameter/hyperparameter priors

The likelihood defined in (2) depends on the unknown parameters $M$ (endmember matrix), $A$ (abundance matrix), $\Sigma$ (endmember variances) and $\Psi$ (noise variances). In order to promote spatial correlations between adjacent pixels of the image, we proposed in [8,9] to introduce $(1 \times N)$ label vectors $z$ indicating the classes of the image pixels. The abundances were then assigned priors depending on these labels and on the $(R \times K)$ matrix of Dirichlet parameters $C = [c_1, \cdots, c_K]$ associated with these $K$ classes. All these prior distributions are briefly recalled below (see also [8, 9]):

- **Label prior**: $f(z) = \frac{1}{\prod_{r=1}^{R}} \exp \left\{ -\beta \sum_{n=1}^{N} \sum_{\ell \in \nu(n)} \delta(z_n - z_\ell) \right\}$ where $\beta > 0$ is the granularity coefficient, $\nu(n)$ denotes the pixel neighborhood, $G(\beta)$ is a normalizing (or partition) constant and $\delta(.)$ is the Dirac delta function (see [11] for a similar choice).

- **Abundance prior**: $f(A|z, C) = \prod_{n=1}^{N} f(a_n|z_n = k, c_k)$ where $a_n|z_n = k, c_k \sim \text{Dir}(c_k)$, for $n \in \mathcal{I}_k$, $\text{Dir}(.)$ denotes the Dirichlet distribution, and $n \in \mathcal{I}_k$ means that $y_n$ belongs to the $k$th class (which is also equivalent to $z_n = k$).

- **Endmember mean prior**: $f(M) = \prod_{n=1}^{N} f(m_n)$, with $m_n \sim N(0, 1)$, $\text{Dir}(c_k)$, where $N(0, 1)$ denotes a truncated Gaussian distribution on $I$, $\bar{m}_n$ is an estimated endmember (resulting from an endmember extraction algorithm such as VCA [14]) and $c_k$ is a fixed variance term defining the confidence that we have on this estimated endmember $\bar{m}_n$.

- **Endmember variance prior**: $f(\Sigma) \propto \prod_{l=1}^{L} \prod_{r=1}^{R} \frac{1}{\sigma_n^2} \exp \left( -\frac{1}{\sigma_n^2} \right)$, $\forall n$.

- **Noise variance prior**: $f(\Psi|\lambda) = \prod_{n=1}^{N} \lambda \exp \left( -\lambda \psi_n^2 \right)$ $\forall n \in \psi_n^2$ where $\lambda$ has a large value ensuring sparsity for $\psi_n^2$. 

2.4. Posterior distribution

The parameters of the proposed Bayesian model are included in the vector $\theta = \{ \theta_p, \theta_h \}$ where $\theta_p = \{ A, M, \Sigma, \Psi \}$ (parameters) and $\theta_h = \{ C, z \}$ (hyperparameters). The joint posterior distribution over the unknown parameter/hyperparameter vector $\theta$ can be computed from the following hierarchical structure

$$f(\theta_p, \theta_h) \propto f(Y|\theta_p) f(\theta_p) f(\theta_h)$$

(3)

where $f(\theta_p, \theta_h) = f(\theta_p|\theta_h) f(\theta_h) = f(A|C, z) f(M) f(C|z) f(z)$, resulting from prior independence between the different parameters.

Unfortunately, it is difficult to obtain closed form expressions for the standard Bayesian estimators associated with (3). These estimators are therefore approximated using an MCMC approach that generates samples asymptotically distributed according to (3). This is achieved using a hybrid Gibbs sampler that sequentially samples the following parameters of interest $A, M, z, \Psi$ and $C$, according to their conditional distributions [16]. Due to the large number of parameters to be sampled and to the complexity of the conditional distributions, we use a CHMC algorithm with good mixing properties [12]. The parameters are finally estimated using the MMSE estimator for $\{A, M, \Sigma, \Psi, C\}$ and the MAP estimator for the labels $z$. The reader is invited to consult [8] for more details.

3. SIMULATION RESULTS ON REAL DATA

The main contribution of this paper is a performance evaluation of the mixing model (1) and its estimation algorithm (referred to as UsGNCM) when applied to a real HS data set, which is the objective of this section. The considered real image was acquired in 2010 by the Hyspex HS scanner over Villelongue, France. The dataset contains $L = 160$ spectral bands, $100 \times 100$ pixels and $R = 4$ components: tree, grass, soil and shadow (see Fig. 1 (a)). Our algorithm is compared with: (i) VCA+FCLS: [14,17], (ii) UsLMM [18] and (iii) AEB [19] (used with 10% image subset and the VCA algorithm).

3.1. Endmember and variability estimation

The UsGNCM algorithm estimates both the mean and variance of each physical element in the scene which provides an EV measure in the considered image. Fig. 2 shows the estimated endmember distributions as blue level areas for each endmember. These distributions are in good agreement with the estimates obtained with VCA, AEB and UsLMM algorithms except for the shadow endmember. Indeed, both AEB and VCA provide a different shadow endmember because they extract the endmembers from the image pixels while UsLMM and UsGNCM estimate both the abundances and endmembers resulting in a better shadow estimate (of lower amplitude). Note finally that the variation is more pronounced for high spectral bands ($l > 80$) which is in agreement with the results presented in [13].

3.2. Abundance Estimation and Image Classification

The fraction maps estimated by the different methods are shown in Fig. 3. Note that a white (black) pixel indicates a large (small) proportion of the corresponding materials. These maps lead to the following conclusions

- UsLMM and UsGNCM present similar abundance estimates with a smoother behavior for the second algorithm (because considering spatial correlations)
kinds of grass. Table 1 finally reports the estimated Dirichlet parameters and the number of pixels for each spatial class when considering the Madonna image. These parameters suggest a highly non-uniform distribution over the simplex which can explain the good performance of the proposed approach.

<table>
<thead>
<tr>
<th>Dirichlet parameters</th>
<th>number of pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_{1k}$</td>
<td>$c_{2k}$</td>
</tr>
<tr>
<td>$k = 1$</td>
<td>1.47</td>
</tr>
<tr>
<td>$k = 2$</td>
<td>13.26</td>
</tr>
<tr>
<td>$k = 3$</td>
<td>0.76</td>
</tr>
<tr>
<td>$k = 4$</td>
<td>37.71</td>
</tr>
<tr>
<td>$k = 5$</td>
<td>23.04</td>
</tr>
</tbody>
</table>

3.3. Noise variances

The proposed algorithm also provides a measure of the noise variance for each observed pixel. This parameter brings an information about pixels that are inaccurately described by the linear mixing model, i.e., allows modeling errors to be quantified. Fig. 1 (c) shows the obtained noise variances for the considered image. This figure shows a higher error in the shadow area and around trees, i.e., for regions where possible interactions between physical components might occur (e.g., tree/soil) resulting in a more complex model than the proposed linear one. Note finally that Fig. 1 (c) highlights the presence of regular vertical patterns that have also been observed in [20] and were associated with a sensor defect or other miscalibration problems.

4. CONCLUSIONS

This paper introduced a Bayesian model for unsupervised unmixing of HS images accounting for EV. The proposed model was based on a generalization of the NCM defined by the endmembers of the scene, their variability controlled by a scale parameter (variance) and the abundances for each pixel of the scene. The observed image was also spatially classified into regions sharing homogeneous abundance characteristics. The physical constraints about the abundances were ensured by choosing a Dirichlet distribution for each spatial class of the image. Due to the complexity of the resulting joint posterior distribution, an MCMC procedure (based on a hybrid Gibbs sampler) was used to sample the posterior of interest and to approximate the Bayesian estimators of the unknown parameters using the generated samples. The proposed algorithm showed good performance when processing real data presenting EV and spatial correlation between adjacent image pixels. It was also shown to be robust to the absence of pure pixels in the observed scene. Future work includes the introduction of endmember variability in nonlinear mixing models.

5. REFERENCES


Fig. 3. Abundance maps estimated by FCLS (first row), UsLMM (second row), AEB (third row) and the proposed UsGNCM (fourth row) for the Madonna image.