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Unsupervised Unmixing of Hyperspectral Images Accounting for Endmember Variability

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Abstract—This paper presents an unsupervised Bayesian algorithm for hyperspectral image unmixing, accounting for endmember variability. The pixels are modeled by a linear combination of endmembers weighted by their corresponding abundances. However, the endmembers are assumed random to consider their variability in the image. An additive noise is also considered in the proposed model, generalizing the normal compositional model. The proposed algorithm exploits the whole image to benefit from both spectral and spatial information. It estimates both the mean and the covariance matrix of each endmember in the image. This allows the behavior of each material to be analyzed and its variability to be quantified in the scene. A spatial segmentation is also obtained based on the estimated abundances. In order to estimate the parameters associated with the proposed Bayesian model, we propose to use a Hamiltonian Monte Carlo algorithm. The performance of the resulting unmixing strategy is evaluated through simulations conducted on both synthetic and real data.

Index Terms—Hyperspectral imagery, endmember variability, image classification, spectral unmixing, Bayesian algorithm, Hamiltonian Monte-Carlo, MCMC methods.

I. INTRODUCTION

HYPERSPECTRAL imaging is a remote sensing technology that collects 3D data cubes composed of 2D spatial images acquired in numerous contiguous spectral bands. Due to the limited spatial resolution of the observed image, each pixel generally consists of several physical elements that are linearly [1], [2] or nonlinearly [3]–[5] mixed. Spectral unmixing (SU) consists of decomposing the pixel spectra to recover these materials, known as *endmembers*, and estimating the corresponding proportions or *abundances* [6]. The linear mixture model (LMM) has received great interest in the literature and has been used intensively for SU. The unmixing is generally performed using two distinct steps: (i) identifying the endmembers using an endmember extraction algorithm (EEA) such as vertex

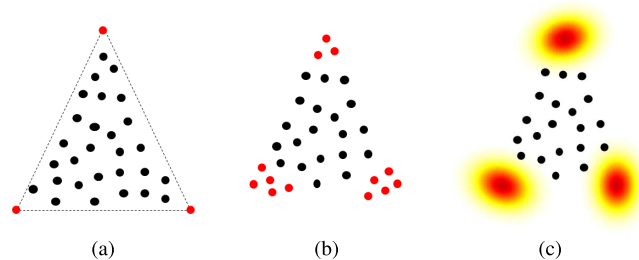


Fig. 1. Simplex representation for (a) endmembers without variability, (b) endmembers as a finite set (or bundle) and (c) endmembers as a distribution.

component analysis (VCA) [7], pixel purity index (PPI) [8] and N-FINDR [9], (ii) estimating the abundances under physical non-negativity and sum-to-one constraints using algorithms such as the fully constrained least squares [2]. Some algorithms also tackle the SU problem in an unsupervised manner, i.e., by jointly estimating the endmembers and the abundances. This is generally achieved under a statistical framework using optimization techniques [10] or Markov chain Monte Carlo (MCMC) simulation methods [6], [11]. The unsupervised algorithms generally provide better results and appear to be less sensitive to the absence of pure pixels [3].

The previous described algorithms provide one endmember spectrum for each physical component present in the image (see Fig. 1(a)). This appears as a clear simplification since in many cases, the endmember spectra vary along the image causing what is known as *spectral variability*. Spectral variability has been identified as one of the most profound sources of error in abundance estimation and is receiving growing interest in the hyperspectral community [12], [13]. Many algorithms have been proposed in the literature to describe this variability. A detailed discussion about these algorithms, their advantages and challenges is available in [12], [13]. Most of these methods can be gathered into two main classes. The first approaches consider each physical material as a set or bundle of spectra (see Fig. 1(b)). One can distinguish between algorithms assuming a known spectral library [14], [15] and those estimating it from the data [16], [17]. SU resulting from these approaches is generally sensitive to the quality of the available or extracted endmember libraries. The second class of methods relies on a statistical representation of the endmembers that are assumed to be random vectors with given probability distributions (see Fig. 1(c)). These approaches

provide a flexible way to incorporate some uncertainties regarding the endmembers [18], [19] and, within an unsupervised context, this choice makes the SU more robust to the absence of pure pixels [20]. Two main statistical models have been considered in the literature to describe endmember variability. The Beta compositional model [21] exploits the physically realistic range of the endmember reflectance by assigning them a Beta distribution. Earlier, the normal compositional model (NCM) was proposed to describe the endmember variability by a Gaussian distribution [18], [20], [22]. An alternative to these parametric models was introduced in [23] for the specific issue of estimating the vegetation fractions in urban environments. In this work, empirical learning of the endmember distributions is conducted from a set of pixels identified as belonging to vegetation and non-vegetation areas. In that sense, it consists of an hybrid method between the two main classes of approaches introduced above, based on a statistical description of the endmember variabilities derived from bundles of spectra.

Adopting a Bayesian perspective, this paper introduces a generalization of this NCM by considering Gaussian variability for the endmembers (as for the NCM) while incorporating an additive Gaussian noise modeling fitting errors (which was not present in the NCM). Moreover, the proposed model considers a different mean and covariance matrix for each endmember to analyze each component of the mixture separately. These parameters are both estimated generalizing the works of [18] and [20] that only estimated the endmembers means or covariances, respectively. Moreover, the endmember fluctuation with respect to the spectral bands is characterized by considering non-identically distributed endmember variances.

Another important point concerning hyperspectral unmixing is the spatial correlation between pixels. Indeed, even if many algorithms consider a pixel-by-pixel context, recent studies have shown the interest of considering spatial information to improve the unmixing quality [24]–[26]. Within a Bayesian framework, this spatial correlation can be introduced using Markov random fields (MRFs) as already shown in [24], [25], and [27]. In this work, a Potts model is considered since it has already shown good performance when processing hyperspectral images [24], [25]. The image is then segmented into regions sharing similar abundance characteristics. Note that this segmentation was also achieved in [10] and [25] by considering Gaussian and Dirichlet distributions for the abundances.

This paper proposes an unsupervised Bayesian algorithm to estimate the parameters associated with an unmixing model accounting for endmember variability. In addition to the abundance Dirichlet priors, it assumes appropriate priors for the remaining parameters/hyperparameters to satisfy the known physical constraints. The joint posterior distribution of the proposed Bayesian model is then derived. However, the classical minimum mean square error (MMSE) and maximum a posteriori (MAP) estimators cannot be easily computed from this joint posterior. A classical way of alleviating this problem is to generate samples asymptotically distributed according to

the posterior using MCMC methods. This goal is achieved in this paper using a Gibbs sampler coupled with a Hamiltonian Monte Carlo (HMC) method. HMC is well adapted for large scale problems, i.e., with a large number of parameters to be estimated [28]. Moreover, this method presents good mixing properties when compared to the classical Metropolis-Hastings algorithm. This paper considers a constrained-HMC (CHMC) that has been introduced in [28, Ch. 5] and successfully used for hyperspectral SU in [11]. This CHMC accounts for inequality constraints which are required to satisfy the physical constraints related to the proposed SU problem.

Main Contributions

The main objective of the paper is to provide a spectral/spatial algorithm to analyze hyperspectral images accounting for endmember variability. The first contribution of the paper is the generalization of the works [18] and [20] by estimating both the mean vector and the variances of the endmembers. This provides important information such as the sensitivity of each physical material in each spectral wavelength. The second contribution is the generalization of the NCM model by introducing an additive noise that accounts for mismodeling such as non-linearity effects. These contributions provide a good spectral analysis of the image. In addition to that, and to exploit the hyperspectral image spatial information, we consider a Potts model that accounts for spatial correlation between adjacent pixels. For each class of this Potts model, we consider a Dirichlet distribution as abundance prior which allows the abundance constraints to be satisfied.

The paper is structured as follows. The unmixing problem considered in this study is formulated in Section II. The different components of the proposed Bayesian model are studied in Section III. Section IV introduces the Gibbs sampler and the CHMC method which will be used to generate samples asymptotically distributed according to the joint posterior of the unknown parameters and hyperparameters. Section V analyzes the performance of the proposed algorithm when applied to synthetic images. Results on real hyperspectral images are presented in Section VI whereas conclusions and future works are reported in Section VII.

II. PROBLEM FORMULATION

The variables used in this paper are described in Table I.

A. Mixing Model and Endmember Variability

This section introduces the proposed mixture model. The classical LMM assumes that the pixel spectrum $\mathbf{y}_n, n \in \{1, \dots, N\}$, where N is the number of pixels in the image, is a linear combination of R deterministic endmembers $\mathbf{s}_r, r \in \{1, \dots, R\}$, corrupted by an additive noise as follows [6], [25]

$$\mathbf{y}_n = \sum_{r=1}^R a_{rn} \mathbf{s}_r + \mathbf{e}_n = \mathbf{S} \mathbf{a}_n + \mathbf{e}_n \quad (1)$$

with

$$\mathbf{e}_n \sim \mathcal{N}(\mathbf{0}_L, \psi^2 \mathbf{I}_L) \quad (2)$$

TABLE I
NOTATION TABLE

N	number of pixels
R	number of endmembers
L	number of spectral bands
K	number of spatial classes
$\mathbf{Y} \in \mathbb{R}^{L \times N}$	spectra of the pixels
$\mathbf{A} \in \mathbb{R}^{R \times N}$	abundance matrix
$\mathbf{M} \in \mathbb{R}^{L \times R}$	endmember means
$\mathbf{\Sigma} \in \mathbb{R}^{R \times L}$	matrix containing the diagonal of endmember covariances
$\mathbf{\Psi} \in \mathbb{R}^{1 \times N}$	noise variances
$\mathbf{z} \in \mathbb{R}^{1 \times N}$	labels
$\mathbf{C} \in \mathbb{R}^{R \times K}$	Dirichlet parameters

where \sim means “is distributed according to”, R is the number of endmembers, \mathbf{y}_n is an $(L \times 1)$ vector representing the n th observed pixel, L is the number of spectral bands, $\mathbf{0}_L$ is an $(L \times 1)$ vector of 0, \mathbf{I}_L is the $(L \times L)$ identity matrix, $\mathbf{a}_n = [a_{1n}, \dots, a_{Rn}]^T$ is the $(R \times 1)$ abundance vector of the n th pixel, $\mathbf{S} = [\mathbf{s}_1, \dots, \mathbf{s}_R]$ is an $(L \times R)$ matrix of endmembers and \mathbf{e}_n is a white Gaussian noise.

The endmembers are generally not constant in the observed image due to environmental conditions or inherent variability [12], [13]. The normal compositional model (NCM) has been widely used in the literature to take into account this variability by assuming random endmembers distributed according to Gaussian distributions. The NCM is defined as

$$\mathbf{y}_n = \sum_{r=1}^R a_{rn} \mathbf{s}_{rn} = \mathbf{S}_n \mathbf{a}_n \quad (3)$$

with

$$\mathbf{s}_{rn} \sim \mathcal{N}(\mathbf{m}_r, \text{diag}(\boldsymbol{\sigma}_r^2)) \quad (4)$$

where $\mathbf{S}_n = [\mathbf{s}_{1n}, \dots, \mathbf{s}_{Rn}]$, $\boldsymbol{\sigma}_r^2 = [\sigma_{r1}^2, \dots, \sigma_{rL}^2]$ is the variance vector of the r th endmember and $\mathbf{M} = [\mathbf{m}_1, \dots, \mathbf{m}_R]$ is the $(L \times R)$ matrix containing the endmember means of the image. Note that (3)-(4) is a general formulation for the NCM that encompasses the model described in [18] since it considers different endmember variances with respect to spectral bands. Note also that the model described in [20] introduces a full covariance matrix for each endmember. However, this covariance matrix was simplified to a diagonal covariance matrix in the algorithmic implementation. In the following, NCM will refer to the model given by (3) and (4) unless otherwise stated.

In this paper, we introduce a new model taking endmember variability into account. More precisely, the proposed model can be seen as a generalized NCM model (GNCM) since it introduces an additional residual Gaussian noise \mathbf{e}_n as follows

$$\mathbf{y}_n = \sum_{r=1}^R a_{rn} \mathbf{s}_{rn} + \mathbf{e}_n = \mathbf{S}_n \mathbf{a}_n + \mathbf{e}_n. \quad (5)$$

The noise \mathbf{e}_n is assumed to be Gaussian, i.e., $\mathbf{e}_n \sim \mathcal{N}(\mathbf{0}_L, \psi_n^2 \mathbf{I}_L)$ and independent from the variables $\mathbf{s}_{1n}, \dots, \mathbf{s}_{Rn}$. The presence of this noise makes the proposed model more robust to mismodeling. Moreover, we consider that the endmember variability is the main source of

randomness in the observed pixel [12], which is ensured by assigning a prior enforcing small values for the noise variances (see Eq. (17)). The model (5) reduces to the NCM (3) for $\psi_n^2 = 0, \forall n$. Thus, it generalizes the model of [18] by considering band-dependent endmember variances for each physical element $\#r$ (i.e., the endmember variance $\sigma_{r\ell}^2$ depends on each spectral band $\#\ell$). This allows the GNCM to capture the spectral variations of each physical element with respect to each spectral band. The GNCM model can also be seen as a generalization of the LMM model used in [6], since the endmember matrix \mathbf{S}_n depends on each observed pixel. This allows the spectral variability to be explicitly introduced while it is fixed with the LMM. Finally, note that the GNCM reduces to the LMM for $\sigma_{r\ell}^2 = 0, \forall \ell, \forall r$ and $\psi_n^2 = \psi^2, \forall n$. The abundance vector \mathbf{a}_n usually represents the spatial coverage of the material in the n th pixel. Therefore, it should satisfy the positivity and sum-to-one (PSTO) constraints associated with both LMM and GNCM

$$a_{rn} \geq 0, \quad \forall r \in \{1, \dots, R\} \quad \text{and} \quad \sum_{r=1}^R a_{rn} = 1. \quad (6)$$

III. HIERARCHICAL BAYESIAN MODEL

This section introduces a hierarchical Bayesian model for GNCM-based unsupervised hyperspectral SU accounting for spectral variability. The Bayesian approach assigns prior distributions to the unknown parameters summarizing the prior knowledge about these parameters. This approach is interesting to alleviate the indeterminacy resulting from ill-posed problems and has been successfully applied for HU [6], [30], [31]. More precisely, if $f(\boldsymbol{\theta})$ denotes the prior distribution assigned to the parameter $\boldsymbol{\theta}$, the Bayesian approach computes the posterior distribution of $\boldsymbol{\theta}$ using the Bayes rule

$$f(\boldsymbol{\theta}|\mathbf{Y}) \propto f(\mathbf{Y}|\boldsymbol{\theta})f(\boldsymbol{\theta}) \quad (7)$$

where \propto means “proportional to” and $f(\mathbf{Y}|\boldsymbol{\theta})$ is the likelihood of the observation vector \mathbf{Y} . The vector $\boldsymbol{\theta}$ is then estimated from this posterior distribution by computing its mean (MMSE estimator) or its maximum (MAP estimator). The following paragraphs introduce the likelihood and the considered prior distributions for $\boldsymbol{\theta}$. The unknown parameters of our model include the $(L \times R)$ endmember mean matrix \mathbf{M} , the $(R \times L)$ matrix $\mathbf{\Sigma}$ gathering the endmember variances (with $\Sigma_{r,\ell} = \sigma_{r\ell}^2$), the $(R \times N)$ abundance matrix \mathbf{A} (whose n th column is $\mathbf{A}_{:n} = \mathbf{a}_n$), and the $(1 \times N)$ vector $\mathbf{\Psi} = [\psi_1, \dots, \psi_N]$.

A. Likelihood

Using the observation model (5), the Gaussian properties of both the noise sequence \mathbf{e}_n and the endmembers, and exploiting independence between the observations in different spectral bands, yield the following likelihood

(see [32, Appendix A])

$$f(\mathbf{y}_n | \mathbf{A}, \mathbf{M}, \boldsymbol{\Sigma}, \boldsymbol{\Psi}) \propto \left(\prod_{\ell=1}^L \Lambda_{\ell n} \right)^{\frac{1}{2}} \exp \left\{ -\frac{1}{2} \boldsymbol{\Lambda}_{:n}^T (\mathbf{y}_n - \mathbf{M} \mathbf{a}_n) \odot (\mathbf{y}_n - \mathbf{M} \mathbf{a}_n) \right\} \quad (8)$$

where $\boldsymbol{\Lambda}$ is an $(L \times N)$ matrix whose elements are given by $\Lambda_{\ell n} = \left(\sum_{r=1}^R a_{rn}^2 \sigma_{r\ell}^2 + \psi_n^2 \right)^{-1}$, $\mathbf{A} = [\mathbf{a}_1, \dots, \mathbf{a}_N]$ is an $(R \times N)$ abundance matrix, and \odot denotes the Hadamard (termwise) product. Moreover, contrary to the LMM, Eq. (8) shows that the elements¹ of $\boldsymbol{\Lambda}$ depend on the pixel abundances and thus on the pixel index $\#n$. This property was also satisfied by the NCM model as previously shown in [18] and [20]. Note finally that the joint likelihood of the observation matrix \mathbf{Y} can be obtained by exploiting independence between the observed pixels

$$f(\mathbf{Y} | \mathbf{A}, \mathbf{M}, \boldsymbol{\Sigma}, \boldsymbol{\Psi}) \propto \prod_{n=1}^N f(\mathbf{y}_n | \mathbf{A}, \mathbf{M}, \boldsymbol{\Sigma}, \boldsymbol{\Psi}). \quad (9)$$

B. Parameter Priors

This section introduces the prior distributions that we have chosen for the parameters of interest.

1) *Classification Prior Modeling*: Many recent works related to hyperspectral imaging have considered spatial correlation between the image pixels to partition the image into homogeneous regions with similar abundances [10], [25]. In this paper, we propose to exploit this correlation by dividing the observed image into K classes sharing the same abundance properties [25]. Each pixel is assigned to a specific class by using a latent label variable z_n that takes its value into a finite set $\{1, \dots, K\}$. The whole set of random variables $\{z_n\}_{n=1, \dots, N}$ forms a random field. The correlation between neighboring pixels is then introduced by considering a Markov random field prior for z_n as follows

$$f(z_n | \mathbf{z}_{\nu(n)}) = f(z_n | \mathbf{z}_{v(n)}) \quad (10)$$

where $\nu(n)$ denotes the neighborhood of the n th pixel as in [25] (a four neighborhood structure will be considered in the rest of the paper), $\mathbf{z}_{v(n)} = \{z_i, i \in v(n)\}$ and $\mathbf{z}_{\setminus n} = \{z_i, i \neq n\}$. As in [24], [25], and [29], this paper considers a Potts model which is appropriate for hyperspectral image segmentation. The prior of \mathbf{z} is then obtained using the Hammersley-Clifford theorem

$$f(\mathbf{z}) = \frac{1}{G(\beta)} \exp \left[\beta \sum_{n=1}^N \sum_{n' \in v(n)} \delta(z_n - z_{n'}) \right] \quad (11)$$

where $\beta > 0$ is the granularity coefficient, $G(\beta)$ is a normalizing (or partition) constant and $\delta(\cdot)$ is the Dirac delta function. The parameter β controls the degree of homogeneity of each region in the image. It is assumed known a priori in this paper. However, it could be also included within the Bayesian model and estimated using the strategy described in [33].

¹The matrix $\boldsymbol{\Lambda}$ depends on the noise and endmember variances.

2) *Abundance Matrix A*: In order to satisfy the constraints (6), the abundance vector should live in the following simplex \mathcal{S}

$$\mathcal{S} = \left\{ \mathbf{a}_n \mid a_{rn} \geq 0, \forall r \text{ and } \sum_{r=1}^R a_{rn} = 1 \right\}. \quad (12)$$

Thus, a natural choice for the prior of \mathbf{a}_n is a uniform distribution on \mathcal{S} [5], [34]. However, we want to define a prior enforcing stronger correlations for spatially close pixels. Therefore, we propose to assign a Dirichlet prior to the abundances of the k th class of the image with Dirichlet parameters $\mathbf{c}_k = (\mathbf{c}_{1k}, \dots, \mathbf{c}_{Rk})^T$ as follows

$$\mathbf{a}_n | z_n = k, \quad \mathbf{c}_k \sim \text{Dir}(\mathbf{c}_k), \quad \text{for } n \in \mathcal{I}_k \quad (13)$$

where $\text{Dir}(\cdot)$ denotes the Dirichlet distribution, and $n \in \mathcal{I}_k$ means that \mathbf{y}_n belongs to the k th class (which is also equivalent to $z_n = k$). This prior allows the data to be located in several different clusters inside the simplex [10]. Moreover, the Dirichlet prior is well suited for modeling the abundances since it takes into account the PSTO constraints.

3) *Endmember Means*: The endmember mean matrix \mathbf{M} contains reflectances that should satisfy the following constraints [11]

$$0 < \mathbf{m}_{rl} < 1, \quad \forall r \in \{1, \dots, R\}, \quad \forall l \in \{1, \dots, L\}. \quad (14)$$

Moreover, it makes sense to assume that the reflectance are close to estimates identified by an EEA. Therefore, we choose a truncated Gaussian prior for each endmember as follows [11], [20]

$$\mathbf{m}_r \sim \mathcal{N}_{[0,1]^L}(\tilde{\mathbf{m}}_r, \epsilon^2 \mathbf{I}_L) \quad (15)$$

where $\tilde{\mathbf{m}}_r$ denotes an estimated endmember (resulting from an EEA such as VCA²) and ϵ^2 is a variance term defining the confidence that we have on this estimated endmember $\tilde{\mathbf{m}}_r$.

4) *Endmember Variances*: As in [18] and [34], the endmember variances have been assigned the following non informative prior

$$f(\boldsymbol{\Sigma}_{:l}) \propto \prod_{r=1}^R \frac{1}{\sigma_{rl}^2} \mathbf{1}_{\mathbb{R}^+}(\sigma_{rl}^2) \quad (16)$$

where we have assumed prior independence between the endmember variances. This distribution introduces some prior knowledge such as the positivity of the endmember variances (the reader is invited to consult [35] for motivations about this prior for scale parameters such as the noise variances).

5) *Noise Variance Prior*: As stated in [12], endmember variability represents the main source of error in spectral mixture analysis. Moreover, hyperspectral images are generally corrupted by a reduced noise level. Therefore, we assume that the noise effect is smaller than the effect of endmember variability.³ This can be achieved by choosing an exponential

²We consider in this paper the VCA algorithm even if other algorithms such as N-FINDR [9] and *pixel purity index* (PPI) [8] could also be investigated.

³This assumption is no longer satisfied in absence of endmember variability. However, even in this case, we show in Section V that the proposed algorithm provides good results for both abundance and endmember estimates.

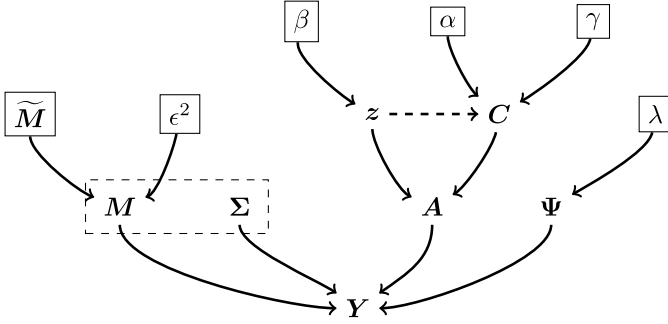


Fig. 2. DAG for the parameter and hyperparameter priors (the fixed parameters appear in boxes). Note that the dashed box defines the statistical distribution of the endmember matrix \mathbf{S} .

prior

$$f(\psi_n^2|\lambda) = \lambda \exp(-\lambda \psi_n^2) \mathbf{1}_{\mathbb{R}^+}(\psi_n^2) \quad (17)$$

where λ has a large value imposing sparsity for ψ_n^2 ($\lambda = 10^7$ in our simulations). We furthermore assume prior independence between the random variables $\psi_n^2, \forall n \in \{1, \dots, N\}$. One interest of choosing the prior (17) is that it avoids identifiability problems between the noise and endmember variances (see [32] for the proof of the problem identifiability). Note that the considered exponential prior includes positivity constraints for the laplace prior that has been widely used in Bayesian contexts to ensure sparsity [36], [37]. Note also that the estimation of ψ_n^2 can be removed from the proposed Bayesian algorithm without changing significantly the estimation performance (see Section V-D). In particular, the proposed model is sufficiently general since the noise effect can be easily removed by setting to zero the noise variances ψ_n^2 .

C. Dirichlet Parameters

The Dirichlet parameters c_k are assigned the following conjugate prior [38]

$$f(\mathbf{c}_k | z_n = k) = \left[\frac{\Gamma(\sum_{r=1}^R c_{rk})}{\prod_{r=1}^R \Gamma(c_{rk})} \right]^\gamma \times \exp\left(-\alpha \sum_{r=1}^R c_{rk} + R\alpha\right) \prod_{r=1}^R \mathbf{1}_{\mathbb{R}^+}(c_{rk}) \quad (18)$$

where α and γ are fixed constants that have been chosen to ensure a non-informative prior (flat distribution) and Γ denotes the gamma function.

D. Posterior Distribution

The parameters of the proposed Bayesian model are included in the vector $\boldsymbol{\theta} = \{\boldsymbol{\theta}_p, \boldsymbol{\theta}_h\}$ where $\boldsymbol{\theta}_p = \{\mathbf{A}, \mathbf{M}, \boldsymbol{\Sigma}, \boldsymbol{\Psi}\}$ (parameters) and $\boldsymbol{\theta}_h = \{\mathbf{C}, \mathbf{z}\}$ (hyperparameters). This Bayesian model is summarized in the directed acyclic graph (DAG) displayed in Fig. 2.

The joint posterior distribution of the unknown parameter/hyperparameter vector $\boldsymbol{\theta}$ can be computed from the following

hierarchical structure

$$f(\boldsymbol{\theta}_p, \boldsymbol{\theta}_h | \mathbf{Y}) \propto f(\mathbf{Y} | \boldsymbol{\theta}_p, \boldsymbol{\theta}_h) f(\boldsymbol{\theta}_p, \boldsymbol{\theta}_h) \quad (19)$$

where $f(\mathbf{Y} | \boldsymbol{\theta}_p, \boldsymbol{\theta}_h) = f(\mathbf{Y} | \boldsymbol{\theta}_p)$ has been defined in (9) and $f(\boldsymbol{\theta}_p, \boldsymbol{\theta}_h)$ is the joint prior of the unknown parameters. Assuming prior independence between the parameters and hyperparameters yields

$$\begin{aligned} f(\boldsymbol{\theta}_p, \boldsymbol{\theta}_h) &= f(\boldsymbol{\theta}_p | \boldsymbol{\theta}_h) f(\boldsymbol{\theta}_h) \\ &= f(\mathbf{A} | \mathbf{C}, \mathbf{z}) f(\mathbf{M}) f(\boldsymbol{\Sigma}) f(\boldsymbol{\Psi}) f(\mathbf{C} | \mathbf{z}) f(\mathbf{z}). \end{aligned} \quad (20)$$

The joint posterior distribution $f(\boldsymbol{\theta}_p, \boldsymbol{\theta}_h | \mathbf{Y})$ can be computed up to a multiplicative constant after replacing (9) and (20) in (19). Unfortunately, it is difficult to obtain closed form expressions for the standard Bayesian estimators associated with (19). In this paper, we propose to use MCMC methods to generate samples asymptotically distributed according to (19) and to build estimators of $\boldsymbol{\theta}$ from these generated samples. Due to the large number of parameters to be sampled, we use an HMC algorithm which improves the mixing properties of the sampler and reduces the required number of iterations to approximate the target distribution [28]. The parameters are finally estimated using the minimum mean square error (MMSE) estimator for $\{\mathbf{A}, \mathbf{M}, \boldsymbol{\Sigma}, \boldsymbol{\Psi}, \mathbf{C}\}$ and the maximum a posteriori (MAP) estimator for the labels \mathbf{z} . The next section defines the proposed sampling procedure based on a hybrid Gibbs sampler including a CHMC method.

IV. HYBRID GIBBS ALGORITHM

The principle of the Gibbs sampler is to generate samples asymptotically distributed according to the conditional distributions of the target distribution (here the posterior (19)) [39]. When a conditional distribution cannot be sampled directly, sampling techniques such as the Metropolis-Hastings (MH) algorithm can be applied. In this paper, we consider a CHMC proposal since it provides better mixing properties than independent or random walk MH moves especially for high-dimensional problems. The next section describes the CHMC algorithm followed by the description of the sampling procedure for the conditional distributions.

A. Constrained Hamiltonian Monte Carlo Method

HMC is used to sample the high dimensional parameter vector of the proposed Bayesian model. It exploits the gradient of the target distribution to improve the quality of the generated samples. Denoting as $f(\mathbf{q})$ (resp. \mathbf{q}) the distribution (resp. d -dimensional variable) to sample, HMC defines the Hamiltonian function after introducing a Gaussian momentum variable \mathbf{p} (that is independent on \mathbf{q}) as follows

$$H(\mathbf{p}, \mathbf{q}) = U(\mathbf{q}) + K(\mathbf{p}) \quad (21)$$

where $U(\mathbf{q}) = -\log[f(\mathbf{q})]$ is the potential energy related to the target distribution $f(\mathbf{q})$ and $K(\mathbf{p}) = \frac{1}{2} \mathbf{p}^T \mathbf{p}$ is the momentum energy which results from an independent centered Gaussian distribution for \mathbf{p} [11]. The evolution of the (\mathbf{q}, \mathbf{p}) samples is determined using the partial derivatives of the Hamiltonian referred to as Hamiltonian equations [28], [40].

For computer implementations, these equations should be discretized which can be done using the leapfrog method that ensures volume preservation and reversibility of the chains [28], [41]. This leapfrog discretization scheme moves the samples by an ϵ stepsize, i.e., from the n th state $(\mathbf{q}^n, \mathbf{p}^n)$ to the $(n+1)$ th state $(\mathbf{q}^{(n+1)}, \mathbf{p}^{(n+1)})$ using N_L iteration steps defined by

$$\mathbf{p}^{(i,n+1/2)} = \mathbf{p}^{(i,n)} - \frac{\epsilon}{2} \frac{\partial U}{\partial \mathbf{q}^T} \left[\mathbf{q}^{(i,n)} \right] \quad (22)$$

$$\mathbf{q}^{(i,n+1)} = \mathbf{q}^{(i,n)} + \epsilon \mathbf{p}^{(i,n+1/2)} \quad (23)$$

$$\mathbf{p}^{(i,n+1)} = \mathbf{p}^{(i,n+1/2)} - \frac{\epsilon}{2} \frac{\partial U}{\partial \mathbf{q}^T} \left[\mathbf{q}^{(i,n+1)} \right]. \quad (24)$$

The resulting samples are accepted with probability ρ given by

$$\rho = \min \left\{ 1, \exp \left[H(\mathbf{q}^n, \mathbf{p}^n) - H(\mathbf{q}^{(n+1)}, \mathbf{p}^{(n+1)}) \right] \right\}. \quad (25)$$

This procedure ensures the resulting samples to be asymptotically distributed according to the target distribution.

In the presence of inequality constraints $(\mathbf{q}^{(i,n\epsilon)} \in [q_l, q_u])$, we adopt the procedure presented in [11] and [28, Ch. 5]. This procedure replaces a sample that violates the constraints at each leapfrog iteration by its symmetric to the bound (see [11] for more details). For example, the candidate $\mathbf{q}^{(i,n)} = q_u + h$ with $0 < h < (q_u - q_l)$ will be replaced by $\mathbf{q}^{(i,n)} = q_u - h$ (and similarly $\mathbf{q}^{(i,n)} = q_l - h$ will be replaced by $\mathbf{q}^{(i,n)} = q_l + h$) when a constraint is not satisfied.

B. Sampling the Parameters/Hyperparameters

Sampling according to the joint posterior (19) is achieved by considering a Gibbs sampler that iteratively generates samples distributed according to the conditional distributions. The obtained hybrid Gibbs sampler consists of six steps that are summarized in Algo. 1, where the conditional distributions associated with the parameters/hyperparameters are derived in [32, Appendix B]. Note that Algo. 1 generates N_{MC} samples for each parameter of interest. However, the MMSE or MAP estimators are computed after removing the first N_{bi} samples belonging to the so-called burn-in period (the length of the burn-in period has been determined using appropriate convergence diagnoses [42]). To accelerate the convergence, the abundances $\mathbf{A}^{(0)}$ and endmember means $\mathbf{M}^{(0)}$ have been initialized using the results of FCLS and VCA, respectively. The initial labels have been generated uniformly in the set $\{1, \dots, K\}$. The other parameters have been initialized as follows $\sigma_{r\ell}^2 = 10^{-3}$, $\psi_n = 10^{-6}$, $c_{rk} = 1$, $\forall r, \forall \ell, \forall n$ and $\forall k$. Note finally that the MCMC approach is robust to local minima and that the results do not depend on the considered initialization.⁴ The interested reader is invited to consult [28], [39], [42] for more details about Gibbs sampler and HMC algorithm, including convergence proofs.

⁴Similar results have been obtained by replacing the prior mean $\tilde{\mathbf{m}}_r$ and the initial endmembers by the results of the N-FINDR algorithm as shown in [32].

Algorithm 1 Hybrid Gibbs Sampler

- 1: Initialization t=0
 - 2: Initialize parameters $\mathbf{A}^{(0)}$, $\mathbf{M}^{(0)}$, $\Sigma^{(0)}$, $\Psi^{(0)}$, $\mathbf{C}^{(0)}$, and $\mathbf{z}^{(0)}$
 - 3: Iterations
 - 4: **for** $t = 1 : N_{MC}$ **do**
 - 5: Parameter update
 - 6: Sample $\mathbf{A}^{(t)}$ from the pdf (37) in [32, Appendix B] using a CHMC procedure
 - 7: Sample $\mathbf{M}^{(t)}$ from the pdf (41) in [32, Appendix B] using a CHMC procedure
 - 8: Sample $\Sigma^{(t)}$ from the pdf (44) in [32, Appendix B] using a CHMC procedure
 - 9: Sample $\Psi^{(t)}$ from the pdf (49) in [32, Appendix B] using a CHMC procedure
 - 10: Hyperparameter update
 - 11: Sample $\mathbf{C}^{(t)}$ from the pdf (52) in [32, Appendix B] using a CHMC procedure
 - 12: Sample $\mathbf{z}^{(t)}$ from the pdf (48) in [32, Appendix B]
 - 13: **end for**
-

V. SIMULATION RESULTS ON SYNTHETIC DATA

This section evaluates the performance of the proposed algorithm with synthetic data. It is divided into four parts whose objectives are: 1) introducing the criteria used for the evaluation of the unmixing quality, 2) presenting the different parameters that are estimated in the proposed unmixing approach, 3) analyzing the behavior of the proposed algorithm as a function of the number of endmembers and the size of the image, 4) comparing the proposed strategy with other state-of-the-art algorithms from the literature.

A. Evaluation Criteria

Abundances and endmembers are known for synthetic images. In this case, the quality of the unmixing strategy can be measured by comparing the estimated and actual abundances by using the average root mean square error (aRMSE) defined by

$$\text{aRMSE}(\mathbf{A}) = \sqrt{\frac{1}{NR} \sum_{n=1}^N \|\mathbf{a}_n - \hat{\mathbf{a}}_n\|^2} \quad (26)$$

where $\|\cdot\|$ denotes the standard l_2 norm such that $\|\mathbf{x}\|^2 = \mathbf{x}^T \mathbf{x}$. The mean of the r th estimated endmember can be compared with the actual one by using RMSE(\mathbf{m}_r) or the spectral angle mapper SAM(\mathbf{m}_r) defined as follows

$$\begin{aligned} \text{RMSE}(\mathbf{m}_r) &= \frac{1}{\sqrt{L}} \|\hat{\mathbf{m}}_r - \mathbf{m}_r\| \\ \text{SAM}(\mathbf{m}_r) &= \arccos \left(\frac{\hat{\mathbf{m}}_r^T \mathbf{m}_r}{\|\hat{\mathbf{m}}_r\| \|\mathbf{m}_r\|} \right) \end{aligned} \quad (27)$$

where $\arccos(\cdot)$ is the inverse cosine operator. Moreover, the global endmember error is evaluated by the averaged

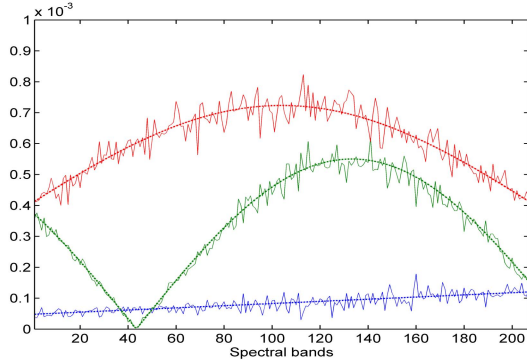


Fig. 3. Actual endmember variances (dashed line) and estimated variances by the proposed UsGNCM (continuous line) for the considered $R = 3$ endmembers.

RMSE (aRMSE) and averaged SAM (aSAM) given by

$$\begin{aligned} \text{aRMSE}(\mathbf{M}) &= \sqrt{\frac{1}{R} \sum_{r=1}^R [\text{RMSE}(\mathbf{m}_r)]^2} \\ \text{aSAM}(\mathbf{M}) &= \frac{1}{R} \sum_{r=1}^R \text{SAM}(\mathbf{m}_r). \end{aligned} \quad (28)$$

Note that the RE and SAM criteria can also be evaluated for the $\#n$ th measured and estimated pixel spectra \mathbf{y}_n , $\hat{\mathbf{y}}_n$ as follows

$$\begin{aligned} \text{RE} &= \sqrt{\frac{1}{NL} \sum_{n=1}^N \|\hat{\mathbf{y}}_n - \mathbf{y}_n\|^2} \\ \text{SAM} &= \frac{1}{N} \sum_{n=1}^N \arccos\left(\frac{\hat{\mathbf{y}}_n^T \mathbf{y}_n}{\|\hat{\mathbf{y}}_n\| \|\mathbf{y}_n\|}\right). \end{aligned} \quad (29)$$

Finally, the Earth movers distance (EMD) criterion (based on the Euclidean distance) has also been considered to simultaneously evaluate the estimated endmembers and abundances [43]. For synthetic data, this criterion compares the estimated parameters to the true ones, while it provides a mutual comparison of the different algorithms for real data (see [43] for more details about EMD).

B. Performance of the Proposed Algorithm

This section considers a 50×50 synthetic image generated according to (5) with $R = 3$ physical elements (construction concrete, green grass and micaceous loam) corresponding to spectral signatures available in the ENVI software library [44]. For each pixel, we generated $R = 3$ endmembers whose means are these ENVI spectral signatures and whose variances are band-dependent and represented in Fig. 3 (dashed lines). This image was partitioned into $K = 3$ classes whose label maps were generated using the Potts model (11) with $\beta = 1.5$ (see Fig. 4). The abundances corresponding to the pixels belonging to a common class share the same Dirichlet parameters (that are reported in Table II) leading to the observed pixels displayed in Fig. 5. Note that the generated abundances were truncated ($a_r < 0.9, \forall r$) to avoid

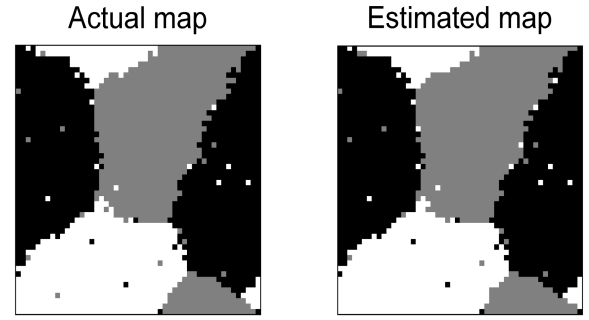


Fig. 4. Actual (left) and estimated (right) classification maps of a synthetic image.

TABLE II
ACTUAL AND ESTIMATED DIRICHLET PARAMETERS
IN EACH SPATIAL CLASS

	Dirichlet parameters					
	c_{1k}	c_{2k}	c_{3k}	\hat{c}_{1k}	\hat{c}_{2k}	\hat{c}_{3k}
$k = 1$	15	15	1	14.97	14.85	1.00
$k = 2$	1	8	8	1.05	8.24	8.19
$k = 3$	3	1	3	3.12	1.02	3.03

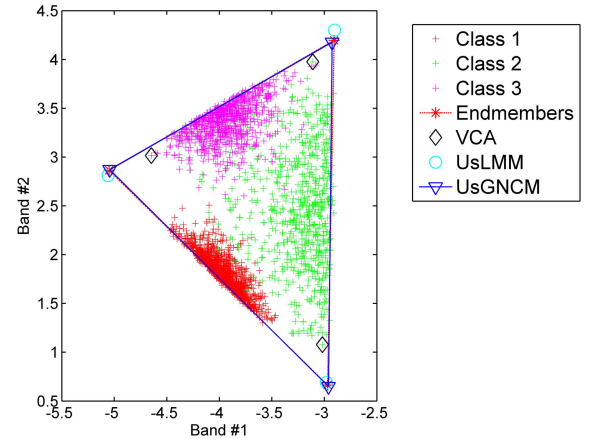


Fig. 5. Classified projected pixels (colored crosses), actual endmembers (red stars), endmembers estimated by VCA (black diamonds), endmembers estimated by UsLMM (cyan circle) and endmembers estimated by UsGNCM (blue triangles).

the presence of pure pixels in the image, which allows us to consider a difficult unmixing problem often encountered in real scenarios [11], [45], [46]. Finally, we considered a noise variance equal to 10^{-7} for all pixels (note that the noise variance has to be smaller than the endmember variances). The proposed unsupervised GNCM-based algorithm, denoted by UsGNCM, was run using $N_{\text{bi}} = 11000$ burn-in iterations and $N_{\text{MC}} = 12000$ iterations.⁵ Fig. 4 (right) displays the estimated classification map obtained with the proposed algorithm. This map is very close to the ground truth shown in Fig. 4 (left). Note that the Dirichlet parameters used in

⁵ N_{MC} represents the total number of samples that have been generated. The MMSE or MAP estimators are computed after removing the first N_{bi} burn-in iterations. The length of the burn-in period has been determined using appropriate convergence diagnoses [42].

TABLE III
USGNCM PERFORMANCE FOR DIFFERENT NUMBER OF ENDMEMBERS (TRUNCATED SIMPLEX)

	aRMSE(\mathbf{A}) ($\times 10^{-2}$)	aRMSE(\mathbf{M}) ($\times 10^{-2}$)	aSAM(\mathbf{M}) ($\times 10^{-2}$)	aRMSE($\mathbf{\Sigma}$) ($\times 10^{-4}$)	aSAM($\mathbf{\Sigma}$) ($\times 10^{-2}$)	EMD
$R = 3$	0.48	0.12	0.28	0.23	7.43	152.3
$R = 4$	0.54	0.21	0.51	0.22	9.16	165.1
$R = 5$	0.80	0.28	0.68	0.31	11.7	198.5
$R = 6$	1.40	0.84	1.65	0.52	14.2	478.8

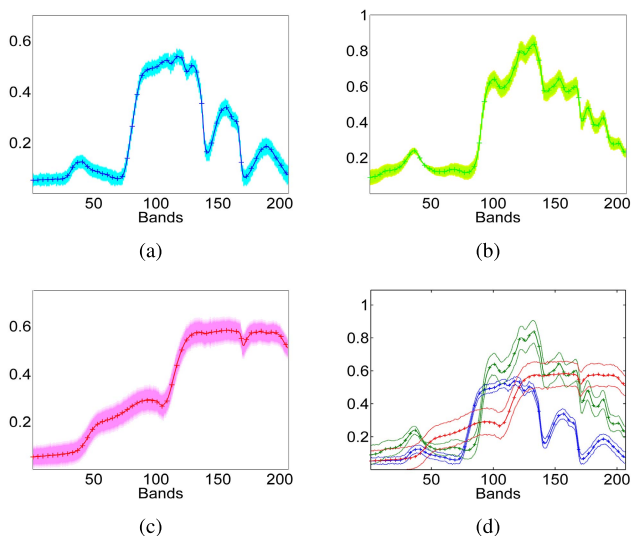


Fig. 6. Actual endmembers (crosses) and endmember means estimated by UsGNCM (continuous lines). The estimated endmember distributions are represented in (a), (b), (c) by colored areas. The bottom-right figure (d) shows the endmembers estimated by UsGNCM $\pm 3\sigma$ (dashed lines).

this simulation correspond to three distinguishable classes that are well separated using the proposed algorithm. The obtained classification results can also be observed with the data projected in the plane associated with the two most discriminant principal components as shown in Fig. 5. The proposed algorithm also allows the Dirichlet parameters to be estimated accurately as shown in Table II.

A significant advantage of the proposed algorithm is its ability to estimate the endmember means and variances. Fig. 5 shows the estimated endmembers obtained using the VCA algorithm (diamonds) [7], the Bayesian unsupervised LMM-based unmixing algorithm (UsLMM, circles) [6] and the proposed UsGNCM approach (triangles). Contrary to the VCA algorithm that provides bad endmember estimates because of the absence of pure pixels in the image, both UsLMM and UsGNCM strategies yield good endmember estimations. As explained before, the good performance of the UsGNCM algorithm can be explained by the fact that it is able to mitigate the endmember variability. Fig. 6 displays the endmember means (continuous lines), the endmember distributions (colored areas in Figs. 6(a), (b) and (c)) and the associated variability intervals defined by mean $\pm 3\sigma$ (Fig. 6 (d)). Fig. 3 displays the actual and estimated endmember variances for the three endmembers that are clearly in good agreement. These results show the good performance of the proposed approach that fully exploits the spatial (segmentation map,

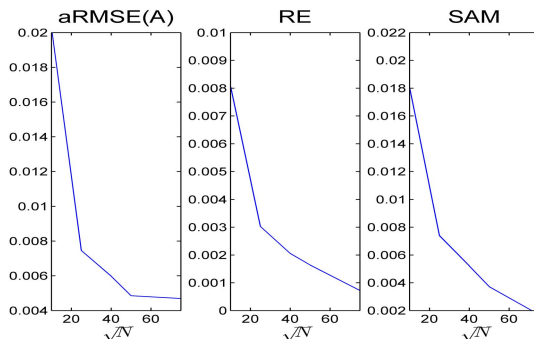


Fig. 7. UsGNCM performance for different numbers of pixels.

abundances and noise variances) and spectral (endmember means and variances) correlations. The next section studies the robustness of the proposed approach with respect to the number of endmembers and pixels (i.e., image size).

C. Performance as a Function of the Number of Endmembers and the Image Size

The UsGNCM algorithm estimates many parameters which might require a lot of observations in order to obtain acceptable performance. The first part of this section deals with this problem by analyzing the proposed algorithm when varying the number of observed pixels. The considered image was generated using the three endmember means and variances considered in Section V-B, the same noise variance, $K = 1$ spatial class and abundances uniformly distributed in the truncated simplex \mathcal{S} (i.e., the abundance are truncated with $a_i < 0.9, \forall i \in 1, \dots, R$ and the Dirichlet parameters are $c_{rk} = 1, \forall r, \forall k$). Fig. 7 shows the obtained aRMSE(\mathbf{A}), RE and SAM when varying the size of the observed image. As expected, the unmixing performance improves by increasing the number of observations. This figure also shows that aRMSE(\mathbf{A}) converges to a constant value for $\sqrt{N} > 50$ while RE and SAM continue to improve when increasing N . Note, however, that the obtained results are quite good for $N \geq 100$.

The second part of this section analyzes the behavior of UsGNCM with respect to the number of endmembers. Table III shows the obtained aRMSE(\mathbf{A}), aRMSE(\mathbf{M}), aSAM(\mathbf{M}), aRMSE($\mathbf{\Sigma}$), aSAM($\mathbf{\Sigma}$) and EMD criteria for $R = \{3, 4, 5, 6\}$. The considered endmember means are construction concrete, green grass, micaceous loam, olive green paint, bare red brick, and galvanized steel metal. These spectra have been extracted from the spectral

TABLE IV
RESULTS ON SYNTHETIC DATA

		Criteria ($\times 10^{-2}$)				($\times 10^{-4}$)	EMD ($\times 10^3$)
		aRMSE (\mathcal{A})	aRMSE (\mathcal{M})	aSAM (\mathcal{M})	aSAM (Σ)	aRMSE (Σ)	
image I_1 (GNM, $K = 1$)	VCA+FCLS	4.78	2.20	4.53	-	-	1.31
	UsLMM	0.52	0.18	0.43	-	-	0.15
	AEB	3.73	2.25	4.90	-	-	1.46
	UsNCM	0.48	0.14	0.31	7.4	0.23	0.17
	UsGNM	0.48	0.12	0.28	7.4	0.23	0.15
	UsGNM $_\ell$	0.47	0.14	0.30	7.4	0.23	0.14
image I_2 (GNM, $K = 3$)	VCA+FCLS	3.71	2.68	6.74	-	-	1.39
	UsLMM	0.76	0.49	0.94	-	-	0.27
	AEB	9.46	4.20	8.72	-	-	2.54
	UsNCM	0.56	0.19	0.43	10	0.27	0.16
	UsGNM	0.48	0.16	0.41	10	0.26	0.15
	UsGNM $_\ell$	0.57	0.24	0.54	10	0.28	0.17
image I_3 (LMM, $K = 3$)	VCA+FCLS	9.51	4.42	8.51	-	-	2.59
	UsLMM	1.01	0.49	1.22	-	-	0.36
	AEB	9.30	5.13	10.92	-	-	2.88
	UsNCM	0.86	0.48	1.15	-	-	0.30
	UsGNM	0.74	0.34	0.74	-	-	0.26
	UsGNM $_\ell$	0.81	0.40	0.91	-	-	0.28

libraries provided with the ENVI software [44]. As previously, the images associated with $R = \{3, 4, 5, 6\}$ were generated with $K = 1$ spatial class and abundances uniformly distributed in the truncated simplex \mathcal{S} with $a_r < 0.9, \forall r$. The endmember variances of the first three physical elements are represented in Fig. 3 and we have considered $(\sigma_4^2, \sigma_5^2, \sigma_6^2) = (\sigma_1^2, \sigma_2^2, \sigma_3^2)$ in this experiment. As expected, increasing the number of endmembers (i.e., increasing R) reduces the estimation performance. However, the obtained results are still acceptable confirming the robustness of UsGNM with respect to the number of endmembers R . Note finally that more simulations, when considering the presence of pure pixels, have also been conducted and showed the good performance of UsGNM (these results are not presented here for brevity but are reported in the technical report [32] available online).

D. Comparison With State-of-the-Art Algorithms

This section evaluates the performance of the proposed UsGNM algorithm for different images. All images were constructed using $R = 3$ endmembers with truncated abundances (with $a_i < 0.9, \forall i \in \{1, \dots, R\}$) to avoid the presence of pure pixels, which allows us to consider a difficult unmixing problem often encountered in real scenarios [11], [45], [46]. The remaining parameters have been defined as follows

- the image I_1 has been generated according to the GNM model with $K = 1$ class and abundances uniformly distributed in the simplex \mathcal{S} . The endmember variances were adjusted as in Fig. 3. The noise variance is $\psi_n^2 = 10^{-7}$.
- the image I_2 is the GNM image used in Section V-B.
- the image I_3 was generated according to the LMM model with $K = 3$ classes. The labels were generated using the Potts model with $\beta = 1.5$ (the same labels as I_2) and the Dirichlet parameters of Table II. The noise variances

vary linearly with respect to the spectral bands with

$$\psi_l^2 = 10^{-4} \left(\frac{4}{L-1}l + \frac{L+3}{L-1} \right), \quad \text{for } l \in [1, \dots, L].$$

These images were processed using different unmixing strategies that were compared to the proposed UsGNM algorithm. More precisely, we considered the following unmixing algorithms

- *VCA+FCLS*: the endmembers are extracted from the whole image using VCA and the abundances are estimated using the FCLS algorithm [2].
- *UsLMM*: the unsupervised Bayesian algorithm of [6] is used to jointly estimate the endmembers and abundances.
- *AEB*: this is the automated endmember bundles algorithm proposed in [17]. We consider a 10% image subset and the VCA algorithm to extract the endmembers. For each pixel, the 3 endmembers that provide the smallest RE are selected.
- *UsNCM*: the proposed unmixing strategy with $\psi_n = 0$ (i.e., the additive noise \mathbf{e}_n of (5) is removed). Note that the resulting model reduces to the NCM and the corresponding unmixing algorithm can be considered as an unsupervised counterpart of the method introduced in [18].
- *UsGNM $_\ell$* : the proposed unmixing strategy with band-dependent noise variances (i.e., $\psi_\ell, \forall \ell$). This is a variant of the proposed algorithm that considers a pixel-independent noise variance in (2). Note that the equations that depend on ψ^2 and the sampling procedure have been modified accordingly. Note also that this algorithm does not provide mismodeling maps contrary to UsGNM.

The first two algorithms provide one estimate for each endmember while the other algorithms estimate endmember variability. Note that the UsNCM and UsGNM $_\ell$ are introduced to study the effect of the additive noise. Table IV reports the quality of the estimated abundances

and endmembers by unmixing the three images with the different algorithms. This table shows bad performance for VCA+FCLS and AEB algorithms which is mainly due to the absence of pure pixels in the considered images and to the variation of the endmember/noise variances with respect to the spectral band. The UsLMM provides good results for the three images. However, it appears to be sensitive to the variation of endmember/noise variances with respect to the spectral band and to the spatial correlations between adjacent pixels. Indeed, the UsLMM did not consider spatial correlation which leads to a performance reduction when processing the images I_2 and I_3 . Note also that the UsLMM algorithm provides one estimate for each endmember and does not take into account the spatial variability of endmembers in the processed images. The best performance is generally obtained by the proposed UsNCM, UsGNM $_{\ell}$ and UsGNM strategies that provide almost similar results. However, the UsGNM algorithm is more robust than UsNCM and UsGNM $_{\ell}$ when processing the LMM image I_3 . Note that when processing I_3 , both UsNCM and UsGNM consider the effect of the colored noise in the LMM to be due to endmember variability. In fact, this effect was expected since the noise variance in (5) does not depend on spectral bands while the endmember variances do. However, this effect does not affect the performance of UsGNM that provides the best results in terms of abundance and endmember estimation as highlighted by the criteria aRMSE, aSAM and EMD. All these results confirm the superiority of the proposed approach in presence of endmember variability, spatial correlation between pixels and in absence of pure pixels in the observed scene.

VI. SIMULATION RESULTS ON REAL DATA

A. Description of the Hyperspectral Data

This section illustrates the performance of the proposed UsGNM algorithm when applied to a real hyperspectral data set. The real image used in this section was acquired in 2010 by the Hypspec hyperspectral scanner over Villelongue, France (00 03'W and 4257'N). The dataset contains $L = 160$ spectral bands recorded from the visible to near infrared (400 – 1000nm) with a spatial resolution of 0.5m [47]. It has already been studied in [11] and [47] and is mainly composed of forested and urban areas. The proposed unmixing algorithm has been applied to two subimages: scene #1 of size 100×100 which is composed of $R = 4$ components: tree, grass, soil and shadow (see Fig. 8 (right)), and scene #2 of size 31×31 which is composed of $R = 3$ components: grass, road and ditch (see Fig. 8 (left)). In addition to the previous studied algorithms, the UsGNM has been also compared to the supervised spectral/spatial BCM based algorithms proposed in [21] and that are denoted by BCM-MH and BCM-QP when considering Metropolis-Hastings (MH) sampler and quadratic programming (QP), respectively. For both BCM algorithms, we have selected the pure pixels manually resulting in a set of spectra for each endmember, as suggested in [21].

B. Endmember and Variability Estimation

The proposed UsGNM algorithm can estimate both the endmember means and variances. Fig. 9 compares the

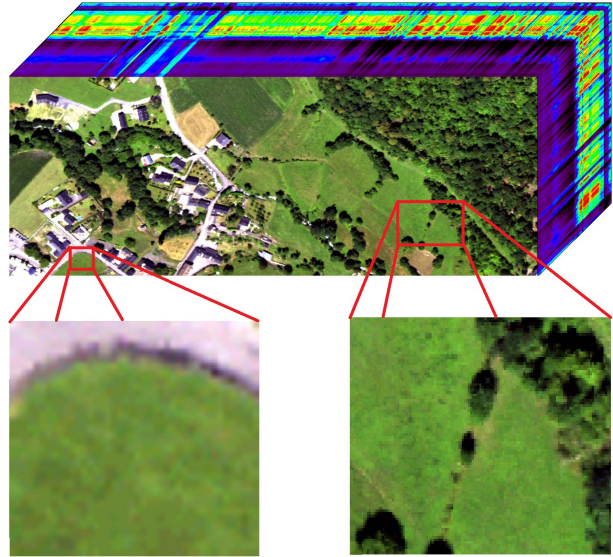


Fig. 8. Real Madonna image and the considered subimages shown in true colors. (Right) scene 1, (left) scene 2.

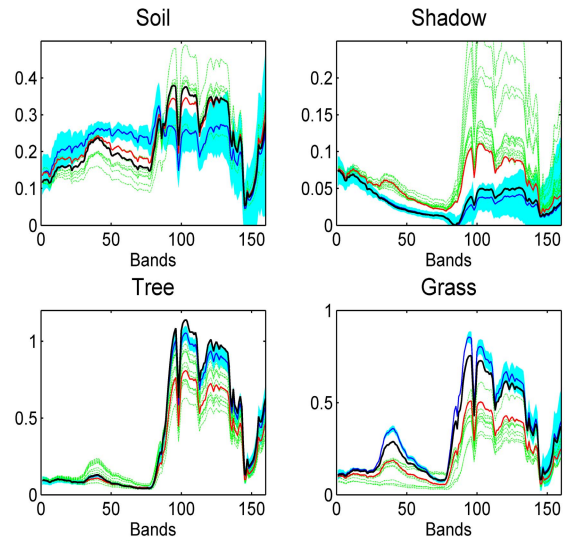


Fig. 9. The $R = 4$ endmembers estimated by VCA (continuous red lines), UsLMM (continuous black lines), AEB (continuous green lines), UsGNM (continuous blue lines) and the estimated endmember distribution (blue level areas) for scene #1 of the Madonna image.

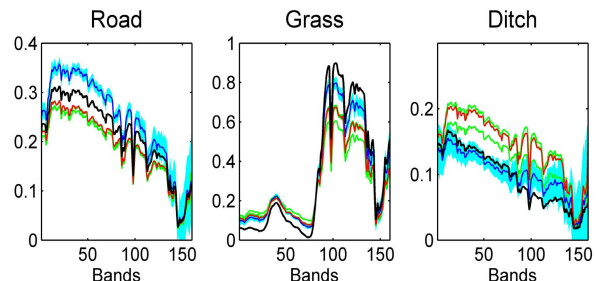


Fig. 10. The $R = 3$ endmembers estimated by VCA (continuous red lines), UsLMM (continuous black lines), AEB (continuous green lines), UsGNM (continuous blue lines) and the estimated endmember distribution (blue level areas) for scene #2 of the Madonna image.

endmember estimates of this algorithm with those obtained with VCA, UsLMM and AEB when considering scene #1. The estimated endmembers are globally in good agreement

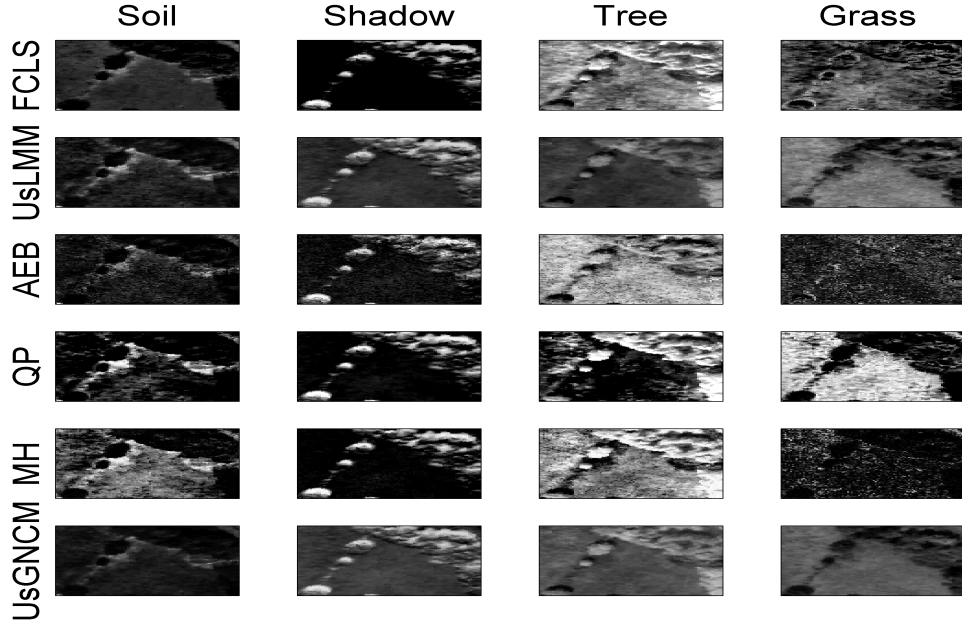


Fig. 11. Abundance maps estimated by FCLS (first row), UsLMM (second row), AEB (third row), BCM-QP (fourth row), BCM-MH (fifth row) and the proposed UsGNCM (sixth row) for the Madonna image.

especially for UsGNCM and UsLMM. Note that VCA (resp. AEB) provides a different shadow endmember because this endmember was extracted as the purest pixel in the image (resp. each sub-image) while UsLMM and UsGNCM estimate both the abundances and endmembers resulting in a better shadow estimate (in the sense that it is less correlated with the other spectra as shown in the technical report [32]). Moreover, the proposed algorithm provides endmember distributions (blue level areas in Fig. 9) which measure the endmember variability in the considered image. The difference between the estimated UsGNCM interval and the AEB spectra is mainly due to the fact that AEB selects the spectral signatures from the image pixels while the UsGNCM is not limited by this constraint. It can be seen from Fig. 9 that the higher relative variation is obtained for the shadow spectrum because of its low amplitude. Moreover, the variation is more pronounced for high spectral bands ($l > 80$) which is in agreement with the results presented in [11]. Fig. 10 shows the obtained endmembers when considering scene #2. This figure presents similar results for UsGNCM and UsLMM, especially for capturing spectral components with low amplitudes as for ditch. Note that UsGNCM $_{\ell}$ and Us-GNCM provided similar visual results (UsGNCM $_{\ell}$ results are not displayed for brevity).

C. Abundance Estimation and Image Classification

The fraction maps of scene #1 estimated by the studied methods are shown in Fig. 11. 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 of spatial correlation)

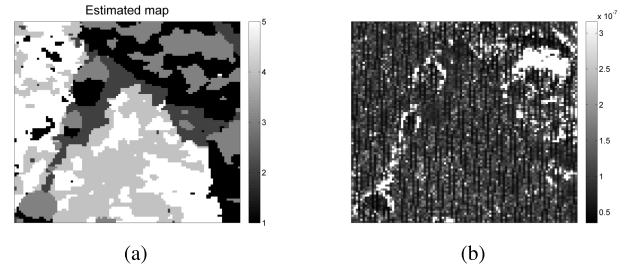


Fig. 12. Estimated maps with the UsGNCM algorithm for the scene #1 of Madonna image. (a) Classification map and (b) noise variances.

- AEB (resp. BCM-MH) is sensitive to the similarity between tree and grass spectra (resp. soil and grass spectra) leading to bad grass maps.

Regarding scene #2, the compared algorithms provide similar abundance maps with lower abundances for UsLMM and UsGNCM. These results are not presented here for brevity (see [32]). The ground truth is not available for these real image, thus, we adopted the procedure of [13] and [21] to quantitatively compare the abundance results (this procedure can be seen as a comparison tool that detects the similarity between the algorithm results). The abundance RMSEs are evaluated after considering the median abundance of all algorithms as a reference. Table V shows the obtained results for the two images that are similar for UsLMM, UsGNCM $_{\ell}$ and UsGNCM which quantitatively confirm the previous conclusions.⁶ In addition to unmixing, UsGNCM also provides a spatial segmentation of the considered scenes as shown in Fig. 12(a) for scene #1 and Fig. 13(a) for scene

⁶The comparison of the different algorithms using EMD have led to the same conclusions. The interested reader is invited to consult [32] for more details about these results.

TABLE V
PERFORMANCE ON REAL IMAGE

Methods	Scene 1			Scene 2		
	RMSE ($\times 10^{-2}$)	RE ($\times 10^{-3}$)	SAM ($\times 10^{-2}$)	RMSE ($\times 10^{-2}$)	RE ($\times 10^{-3}$)	SAM ($\times 10^{-2}$)
VCA+FCLS	12.4	16.9	5.6	2.4	11	3.4
UsLMM	13.7	6.3	2.7	19	8	2.9
AEB	19.1	6.1	2.6	2.8	9	3.0
UsGNCM	12.1	6.4	2.7	15.2	8	2.9
UsGNCM _ℓ	12.5	6.4	2.7	15.2	8	2.9
BCM-QP	18.9	12.4	3.5	4.9	13	3.3
BCM-MH	17.6	14.7	4.5	4.6	14	3.4

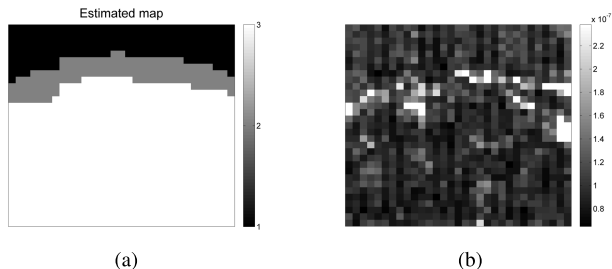


Fig. 13. Estimated maps with the UsGNCM algorithm for the scene #2 of Madonna image. (a) Classification map and (b) noise variances.

TABLE VI
ESTIMATED DIRICHLET PARAMETERS FOR THE
MADONNA IMAGE (SCENE 1)

	Dirichlet parameters				number of pixels
	\hat{c}_{1k}	\hat{c}_{2k}	\hat{c}_{3k}	\hat{c}_{4k}	
$k = 1$	1.47	4.59	10.98	4.39	2144
$k = 2$	13.26	14.05	15.96	14.22	1064
$k = 3$	0.76	7.97	3.75	1.36	1502
$k = 4$	37.71	76.11	84.06	99.97	2483
$k = 5$	23.04	57.70	89.82	99.93	2807

#2. These classification clearly highlight the area of each physical element in the scene. Indeed, for scene #1 we have 5 classes that represent tree, soil, shadow, and grass zones while for scene #2 we have 3 classes representing road, ditch and grass areas. Table VI finally reports the estimated Dirichlet parameters and the number of pixels for each spatial class when considering scene #1. These parameters suggest a highly non uniform distribution over the simplex which promote the use of the proposed approach.

D. Reconstruction Errors

This section compares the proposed UsGNCM strategy to state-of-the-art algorithms in terms of signal reconstruction. Table V shows the obtained RE and SAM for the studied strategies.⁷ As expected, the AEB algorithm, whose objective is to minimize the RE criteria, shows better results when compared to the other approaches for scene #1. However, UsLMM, UsGNCM_ℓ and UsGNCM present good results

⁷The estimated endmember mean is considered for UsGNCM. The endmember mean of each set is considered for the BCM approaches.

especially for scene #2 where they outperform AEB. Indeed, UsLMM and UsGNCM are statistical algorithms estimating endmembers that are not necessarily pixels of the image, which makes them more flexible than VCA, AEB and BCM (that require the presence of pure pixels in the image).

E. Residual Components

The proposed UsGNCM 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 a linear formulation, i.e., allows modeling errors to be quantified. Fig. 12(b) shows the obtained noise variances for the scene #1. 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. The noise variances associated with the scene #2 are shown in Fig. 13(b). This figure shows a higher error near the ditch area which might be due to the presence of nonlinearities as explained in [11]. Note finally that both Fig. 12(b) and Fig. 13(b) highlight the presence of regular vertical patterns that have also been observed in [48] and were associated with a sensor defect or other miscalibration problems.

VII. CONCLUSIONS

This paper introduced a Bayesian model for unsupervised unmixing of hyperspectral images accounting for spectral variability. The proposed algorithm was based on a generalization of the normal compositional model and includes an additive Gaussian noise for modeling errors. This algorithm estimated the endmembers of the scene, their variabilities provided by their variances and the corresponding abundances. The observed image was also spatially segmented into regions sharing homogeneous abundance characteristics. The physical constraints of 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, a Markov chain Monte Carlo procedure based on a Gibbs algorithm was used to sample the posterior of interest and to approximate the Bayesian estimators of the unknown parameters using the generated samples. The sampling was achieved using an Hamiltonian Monte Carlo method which is well suited for problems with a large number of parameters.

The proposed algorithm showed good performance when processing data presenting endmember variability, spatial correlation between pixels and in absence of pure pixels in the observed scene. The proposed algorithm fully exploits both the spatial dimension (segmentation, abundance and noise estimation) and the spectral dimension (estimation of endmember means and variances). Future work includes the study of endmember variability for nonlinear mixing models. Considering spectral correlation jointly with endmember variability is also an interesting issue which would deserve to be investigated.

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