LIDAR-AIDED TOTAL VARIATION REGULARIZED NONNEGATIVE TENSOR FACTORIZATION FOR HYPERSPECTRAL UNMIXING

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ABSTRACT

Hyperspectral unmixing (HU) is an important research field in hyperspectral image processing. In recent years, Nonnegative Tensor Factorization (NTF)-based methods have gained great importance in remote sensing imagery, especially hyperspectral unmixing, regardless of any information loss. Nevertheless, NTF has some disadvantages, such as signal-to-noise ratio (SNR) and noncovexity conditions. Mentioned problem can be solved by introducing some spatial regularizations. On the other hand, LiDAR data provides Digital Surface Model (DSM) information gives accurate elevation information about the observed scene. Moreover, total variation (TV)-based regularization provides piecewise smoothness and it preserve edge structure information in the abundance maps. However, this property could be inappropriate for pixels located in edges. LiDAR-DSM alleviates this problem by contributing neighboring objects pixels differently. In this paper, we proposed a simple yet efficient HU framework that incorporates LiDAR data with TV regularized matrix–vector NTF method (LiMV-NTF-TV). Experimental studies are carried out on simulation data sets and demonstrate that the proposed framework can provide better abundance estimation maps.

Index Terms **—** Hyperspectral (HS) image, Light Detection And Ranging (LiDAR), data fusion, spectral unmixing, Total Variation, NTF, ADMM.

1. INTRODUCTION

In recent decades, hyperspectral unmixing has been one of the main research areas in remote sensing imagery [1]. Hyperspectral unmixing process aims to estimate endmembers and their corresponding abundance maps. Moreover, thanks to the recent advanced sensor technology, an acquisition of LiDAR and hyperspectral data of a captured scene can be obtained simultaneously. However these modules, which are valuable, have some drawbacks. Hyperspectral imagery is not able to distinguish distinct objects which are made of from similar materials and its effectiveness is not enough in cloud-shadow areas. On the other hand, LiDAR data cannot discriminate different materials in the image that are at the same altitude [2]. The LiDAR data provides Digital Surface Model (DSM) information that is not affected any weather condition. Thus, both modalities are complement to each other.

Total variation (TV) constraint preserves edge structure information and assumes that a pixel has only similarity with its four closest neighbors [3]. Sometimes HS image provides sufficient spatial-spectral information about the observed scene. However, this information could not be sufficient in some cases to correctly discriminate neighboring but different objects. In that case, LiDAR-DSM data can be more useful to obtain height information. And so, spatial regularization weights can be estimated by using LiDAR-DSM data. Tatsumi et. al. [4] proposed LiDAR data-weighted TV spatial regularization for HU with Nonnegative Matrix Factorization (NMF).

Compared with 2D matrix form, a Third-order tensor is more appropriate for representing hyperspectral image. Recently, several NTF-based approaches have been presented for hyperspectral unmixing since they do not cause any loss of information in hyperspectral images. Additionally, bad conditions like low-SNR and bad weather cause nonuniquesness of tensor decomposition. Embedding LiDAR-DSM data information to tensor factorization is an effective procedure to alleviate the drawbacks of NTF. In this study, we take LiDAR data information into consideration during unmixing process in tensor factorization.

There are several studies using LiDAR data for unmixing. In [5], a novel Coupled High-Order Tensor Factorization (CHOTF) model is proposed to achieve better classification classification result by using hyperspectral and LiDAR data fusion. Li et. al. [6], create high-order tensor feature by using LiDAR data for classification task. Also in [7], tensor decomposition is used to select important features from raw LiDAR point cloud. Xiong et. al. [8] proposed it is stated that total variation (TV)-based spatial regularization method to preserve edge information in HU process by using NTF. Rasti et. al. [9] introduced a orthogonal total variation component analysis (OTVCA) approach to increase classification accuracy by combining LiDAR and HSI information.

In this study, we propose LiDAR data-aided hyperspectral unmixing using TV-regularized NTF to increase the spatial resolution of the hyperspectral images. The obtained convex optimization problem is solved by using ADMM. The advantage of usage of LiDAR-DSM regularization is also demonstrated.

The remainder of this paper is organized as follows. In Section II, inspired related work are explained. In Section III, an effective usage of LiDAR-DSM data information is adopted to tensor total variation algorithm. Experimental studies are explained in Section 4. Finally, Section 5 concludes the paper.

2. RELATED WORK

As a combination of Canonical Polyadic decomposition (CPD) and Tucker decomposition, Block Term Decomposition (BTD) is used in this study. BTD provides a more flexible modeling opportunity. Qian et al. [10] proposed an MV-NTF model that processes an HS image under BTD tensor framework. This approach decomposes the observed HSI into the sum of R component tensors, which can be decomposed into a low-rank matrix (abundance map) out product with a vector (endmember). Several experiments have proved the superiority of this method over many unmixing algorithms based on NMF

Xiong et al. [8] added total variation constraint to [10] and construct an MV-NTF-TV approach that preserving edges while promotes piecewise smoothness between adcacency pixels. The cost function of MV-NTF-TV can be written as follows:

$$\min_{A,B,C}\frac{1}{2}\left\|\mathcal{Y}-\sum_{r=1}^{R}(\mathbf{A}_r\mathbf{B}_r^T)\circ\mathbf{c}_r\right\|_F^2+\frac{\delta}{2}\left\|\mathbf{1}_{IxJ}-\mathbf{AB}^T\right\|_F^2 + \lambda\sum_{r=1}^{R}(\mathbf{A}_r\mathbf{B}_r^T)_{TV} \quad (1)$$

where $\mathcal{Y}\in\mathbb{R}^{LxJxK}$ HIS matrix cube, $\boldsymbol{A}_r\boldsymbol{B}_r^T\in\mathbb{R}^{LxJ}$ abundance map, $\boldsymbol{c}_r\in\mathbb{R}^{Kx1}$ endmembers. $\circ$ is Outer Product, $\boldsymbol{A}=[\boldsymbol{A}_1 \ldots \boldsymbol{A}_R]$ and $\boldsymbol{B}=[\boldsymbol{B}_1 \ldots \boldsymbol{B}_R]$. where λ regularization parameters and $\|.\|_{TV}$ is total variation regularization. To get better abundance estimation, more spatial information can be used from LiDAR-DSM data. This will be explained in the next section.

3. LiDAR-BASED MATRIX-VECTOR NTF-TV FOR HYPERSPECTRAL UNMIXING (LiMV-NTF-TV)

3.1. LiDAR-DSM-aided Weight Function

In this paper, a general spectral unmixing framework that allows external LiDAR-DSM data to calculate weights and contribute the spatial regularization is developed. Spatial constraint terms express that the abundance maps are smooth, but they cannot preserve the edge information in the hyperspectral imagery. Existing unmixing approaches often ignore this edge structure or they derive this edge information from its own hyperspectral image. However, this information can be affected by too much noise and lighting changes. Thus, this may cause inappropriate spatial information in the unmixing procedure. By imposing some spatial constraints on the tensor decomposition, this problem will be efficiently alleviated. TV-regularization can be employed to handle the piecewise smoothness between the spatial neighborhood pixels by using hyperspectral and LiDAR-DSM data. As shown in Figure 1. LiDAR-DSM information can be incorporated into the unmixing process by weighting the TV-regularization as a spatial constraints. This weight information are embedded into the original MV-NTF-TV to make more feature contribution to unmixing process.

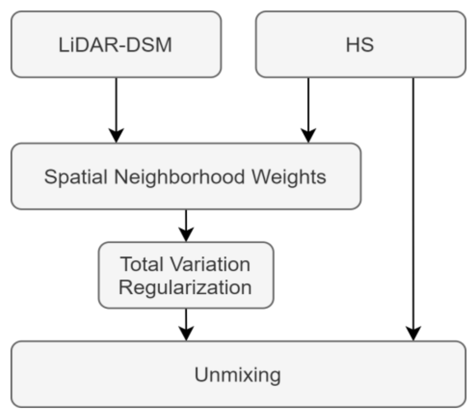


Figure 1. Proposed Framework

In this weight function, DSM can be useful to switch off the spatial constraint by forcing $w_{ij}=0$ for the couples of pixels (i,j) located in these edges. Hence, LiDAR-DSM information preserves sharp transitions from being zero. Thereby, neighboring pixels located in edges can contribute differently to the spatial regularization term.

Several weighting functions can be defined [4]. In this study, we construct $\mathrm{w_{ij}}-\mathrm{DSM}$ weighting function as follows:

$$w_{ij} = \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{\mathrm{k}=1}^{\mathrm{K}} \exp(-(h_{\mathrm{i,j}} - \mathrm{h_k}) - \|\mathcal{Y}_{\mathrm{i,j}} - \mathcal{Y}_{\mathrm{k}}\|) \quad (2)$$

where $h_{\mathrm{i,j}}$ is the DSM data values, $\mathcal{Y}_{\mathrm{i,j}}$ are the spectral information of hyperspectral daha, N and M are the row and column size of the data and K is the number of endmembers.

$$\min_{A,B,C,E,U,V} \frac{1}{2}\left\|\mathcal{Y} - \sum_{r=1}^{R}(\mathbf{A}_r\mathbf{B}_r^T) \circ \mathbf{c}_r\right\|_F^2 + \frac{\delta}{2}\|\mathbf{1}_{IxJ} - \mathbf{A}\mathbf{B}^{\boldsymbol{T}}\|_F^2 + \boldsymbol{\lambda}\sum_{r=1}^{R}(\mathbf{E}_r)_{TV} + \frac{\boldsymbol{\mu}}{\mathbf{2}}\sum_{r=1}^{R}\|\boldsymbol{E}_r - U_r\mathbf{V}_r^T\|_F^2 + \frac{\boldsymbol{\mu}}{\mathbf{2}}(\|\boldsymbol{U} - \mathbf{A}\|_F^2 + \|\boldsymbol{V} - \mathbf{B}\|_F^2) \quad (3)$$

$$\boldsymbol{s.t} \qquad \boldsymbol{A \geq 0}, \ \boldsymbol{B \geq 0}, \ \boldsymbol{C \geq 0}, \ \boldsymbol{U \geq 0}, \ \boldsymbol{V \geq 0}$$

$\mathrm{w_{i,j}}$ weights are used as a coefficient of $\mathrm{E_r}$ in Eq. (3). By using rhis weighting function, higher order relationships with spatial regularization can be introduced additional relational information which provide better HU result on tensor factorization.

4. EXPERIMENTAL RESULTS

Synthetic data set is used to evaluate the proposed LiDAR-DSM-based matrix-vector NTF method. SIM data has been selected by randomly selecting five different materials with their endmember spectra from the USGS spectral library. This data has been widely used to investigate the performance of various unmixing algorithms. A synthetic subset image of size 64 × 64 and 81 × 81 has been sampled as in [4]. Synthetic DSM is obtained by assigning each area a different height value. And then, this data has been corrupted by an addition of Gaussian noise with SNR = 20 dB, 30 dB and 50 dB, respectively. The initialization method of the proposed algorithm has critical role since the tackled optimization problem is not convex. We have initialized abundances during the experiments using both random and Fully Constrained Least Squares (FLSU) methods, respectively. All scaling factor is set to one and the five reference endmembers in each pixel were extracted using VCA. Parameters μ and λ are tuned empirically with 3 different value for each. For μ; 0.5, 3, 25 and for λ; 0.0001, 0.25 and 1 values are used. μ and λ parameters have big impact on the accuracy of estimated abundances. These values were chosen from a set of numbers with a larger number of members. Table 4.1.and Table 4.2. show the results of 64 x 64 and 81 x 81 image size of systhetic data set for proposed framework with different noise levels and different initialization process, respectively. It can be seen from Table 4.1. and Table 4.2. that adding the regularization of LiMV-NTF-TV provides better improvement results.

TABLE 4.1: LiMV-NTF-TV RESULTS FOR 64 X 64 IMAGE SIZE

		RMSE	
		20dB	30dB
Random Initialization	**LiDAR-NTF**	**0,121376**	**0,121638**
	MV-NTF-TV	0,135287	0,133842
FCLS Initialization	**LiDAR-NTF**	**0,137966**	**0,139515**
	MV-NTF-TV	0,143437	0,143212

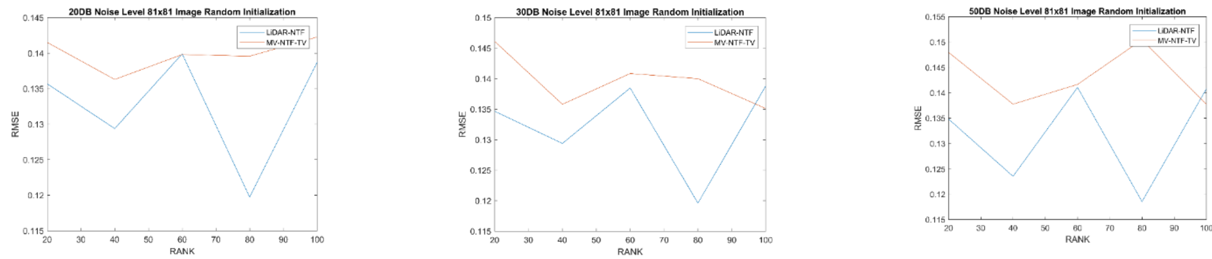
TABLE 4.2: LiMV-NTF-TV RESULTS 81 X 81 IMAGE SIZE

		RMSE	
		20dB	50dB
Random Initialization	**LiDAR-NTF**	**0,119726**	**0,118535**
	MV-NTF-TV	0,136287	0,137737
FCLS Initialization	**LiDAR-NTF**	**0,129078**	**0,104353**
	MV-NTF-TV	0,140204	0,127369

Table 4.1. shows that random and FCLS initialization results of the 64 × 64 image size of the simulation data for two different SNR values. Same procedure are carried out for 81 × 81 image size of the same simulated data set for different SNR values, respectively. Obtained results are depicted in Table 4.2.

Also, Figure 2. shows RMSE change for different rank values from 20 to 80. It is easily seen that in, when the rank values are increased, the RMSE values are decreased.

This study propose a general framework to incorporate external LiDAR-DSM data information into a spatially regularized unmixing approach. From the experimental results, It can be seen that proposed methodology provides better performance as the image size increases. Becasue large image size implies the richness of the structural information within it. Experimental studies demonstrate that LiMV-NTF-TV gives better unmixing result.



a) b) c)

Figure 2. RMSE with respect to the rank of abundance matrix. a) 20dB_81x81 image b) 30dB_81x81 image c) 50dB_81x81 image.

4. CONCLUSION

In this study, hyperspectral unmixing based on tensor factorization is performed with the help of LiDAR-DSM data. Thus, adding new LiDAR-DSM based spatial regularization can provide better abundance map estimations. Experiments on synthetic data are conducted. This paper deeply focused on TV-like regularizations but the proposed framework has a great potential to be adapted with other spatial regularizations. More detailed experimental results will be done in the future work. This framework allows to take advantages of the complementary characteristics of both modalities.

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