Hierarchical Compressed Subspace Clustering of Infrared Single-pixel Measurements

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Abstract

This paper proposes a hierarchical approach to design the sensing matrix of the single-pixel camera architecture (SPC), such that the pixel clustering task can be performed directly using the compressed infrared SPC measurements, i.e., without needing to perform a previous reconstruction step. Specifically, a sensing matrix is designed to extract features directly from the compressed measurements in each stage of the hierarchical model. Lastly, the final segmentation map is obtained through the majority voting method in the partial clustering results at each hierarchy step. Through simulations and experimental proof-of-concept implementation, we demonstrate that the proposed imaging system, together with the sensing protocol and the computational algorithm, represents an efficient alternative to estimate clustering maps without relying on oversampling sensing protocols.

1. Introduction

Spectral imaging (SI) acquires two-dimensional spatial information of a scene across a range of spectral wavelengths which allows the identification of several target features [16]. In particular, spectral clustering is an unsupervised technique that has been successfully employed in SI classification when the labeled samples are unavailable or difficult to acquire [10, 12, 13]. This classification task usually improves as the number of spectral bands increases [6]. However, this requires sensing more information, which makes spectral data acquisition and processing challenging under traditional scanning-based methods.

Compressive spectral imaging (CSI) has emerged as a SI approach that acquires compressed projections of the whole data cube instead of directly measuring all the voxels [14, 15]. CSI allows to detect and reduce the dimensionality of the scene in a single step. Consequently, the cost of sensing, storage, transmission, and processing spectral images using CSI devices is significantly reduced [1, 4].

Several works in CSI have focused on improve the quality reconstruction results [2, 3, 7, 11]. However, they are computationally expensive and present a high convergence time [19]. It is worth highlighting that traditionally, the scenes are acquired inside the visible spectrum range for spectral classification works, i.e., beginning at 400 nm.

In this work, we propose a hierarchical approach to design a sensing matrix of the single pixel camera (SPC) [5] such that clustering features are extracted directly from the acquired compressed measurements. Specifically, at each level of the hierarchy, a sensing matrix is designed as the product of a Hadamard matrix and a decimation matrix. This decomposition allows obtaining a set of features directly from the compressed measurements exploiting the properties of the Hadamard matrix. In the proposed approach, the decimation matrix at a given level is designed to group more similar spatial features than the previous level. Therefore, the composite sensing matrix has more sampling vectors and it is intended to provide more features than those obtained in the previous level. Lastly, the final segmentation map is obtained by performing majority voting on the partial clustering results obtained using the set of features of each hierarchy level.

2. CSI Acquisition System

The proposed CSI clustering approach in this paper is performed on the compressed measurements acquired with the single-pixel camera (SPC), which employs a point spectrometer to obtain the spectral information [5]. Specifically, the objective lens focuses the input 3D scene $\mathbf{F}$, with N_λ spectral bands and $M \times N$ spatial pixels, onto the coded aperture $\mathbf{H} \in \mathbb{R}^{M\times N}$, that spatially modulates each spectral pixel. The sensing process can be expressed as

$$\mathbf{Y} = \mathbf{H}\hat{\mathbf{F}} + \boldsymbol{\epsilon}, \tag{1}$$

where $\mathbf{Y} \in \mathbb{R}^{K\times N_\lambda}$ is the compressed measurements for K-shots, $\mathbf{H} \in \mathbb{R}^{K\times N_x N_y}$ is the coded aperture with $\mathbf{H} \in \{1, 0, -1\}$, $\hat{\mathbf{F}} \in \mathbb{R}^{N_x N_y \times N_\lambda}$ is a matricial version of the 3D datacube $\mathbf{F} \in \mathbb{R}^{N_x\times N_y\times N_\lambda}$, and $\boldsymbol{\epsilon} \in \mathbb{R}^{K\times N_\lambda}$ represents the additive noise. Furthermore, it is possible to capture several snapshots by employing a different coded aperture pattern each time. The compression ratio in this model is given by $\gamma = \frac{K}{MN}$, where $\gamma \in [0, 1]$.

Sensing Matrix Design: Taking into account the structure of Hadamard matrices, the work in [17] proposes to design the sensing matrix for each band $\mathbf{H}$ as

$$\mathbf{H} = \mathbf{W}\boldsymbol{\Delta}, \tag{2}$$

where $\mathbf{W} \in \{-1, 1\}^{K \times K}$ is a Hadamard matrix, and $\boldsymbol{\Delta} \in \mathbb{R}^{K \times MN}$ is a decimation matrix. Recently, a fast spectral image recovery method was introduced in [8], where authors proposed to design $\boldsymbol{\Delta}$ by obtaining superpixels from an RGB image which was acquired as side information. Specifically, the method named *FMR* takes advantages of the fact that the inverse of a Hadamard matrix is its transposes and perform a fast low-resolution reconstruction for each spectral band as $\tilde{\mathbf{f}}_l = (1/K)\hat{\boldsymbol{\Delta}}\mathbf{W}^T\mathbf{y}_l = (1/K)\hat{\boldsymbol{\Delta}}\mathbf{W}^T\mathbf{W}\boldsymbol{\Delta}\mathbf{f}_l \approx \mathbf{f}_l$ Note that, instead of performing the complete reconstruction, it is possible to directly extract features from the compressed measurements. In particular, features from the l-th band can be obtained as $\bar{\mathbf{f}}_l = \mathbf{W}^T\mathbf{g}_l = \boldsymbol{\Delta}\mathbf{f}_l$, where $\bar{\mathbf{f}}_l$ contains the average spectral information of pixels grouped in segments given by the structure of the downsampling matrix $\boldsymbol{\Delta}$. It is important to note that, similar as in [8], in the following sections we assume that $K = N_{seg}$.

3. Proposed CSI Clustering

Taking into account the sensing matrix construction approach presented in (2), it is possible to design the downsampling matrix $\boldsymbol{\Delta}$ to efficiently extract clustering features from the compressed measurements.

Downsampling Matrix Design: In general, the binary matrix $\boldsymbol{\Delta} \in \mathbb{R}^{N_{seg} \times MN}$ groups the $M \times N$ spectral pixels in N_{seg} segments, such that each component of the vector $\bar{\mathbf{f}}_l = \boldsymbol{\Delta}\mathbf{f}_l$ contains the average spectral information of pixels grouped in one segment. More formally, denote $\mathbf{p}^e$ as the vector of size n_e containing the indices of all pixels belonging to the e-th segment. Then, the nonzero values of the $e - th$ row of $\boldsymbol{\Delta}$, denoted in vector form as $(\delta_e)^T$, are determined by the entries of $\mathbf{p}^e$ and the value of n_e as:

$$(\delta_e)^T_{(\mathbf{p}^e)_j} = \frac{1}{n_e}, \quad \text{for } j = 1, \cdots, n_e, \tag{3}$$

where $(\delta_e)^T_{(\mathbf{p}^e)_j}$ denotes the position in δ_e indexed by the $j - th$ entry of the vector $\mathbf{p}^e$. The main idea of the proposed design of $\boldsymbol{\Delta}$ is to group pixels such that similar spectral information is taken into account. As only the compressed measurements are available and we do not have information from VIS spectrum (we are only interested in NIR), we propose to design $\boldsymbol{\Delta}$ in an iterative hierarchical fashion such that $Nseg$ increases (fewer pixels are grouped in one square (regular) segment) in each iteration. At each iteration it, N_{seg} is selected as $N_{seg}^{(it)} > N_{seg}^{(it-1)} > \cdots > N_{seg}^{(1)}$ such as

Algorithm 1 Downsampling Matrix Design

Require: $\bar{\mathbf{F}}$, N_{seg}, $\mathbf{U}$. **Ensure:** $\boldsymbol{\Delta}$

$k_{idx} \leftarrow$ RegularSegms$(\mathbf{U}, N_{seg})$ ▷ k_{idx} contains the segment labels
$\boldsymbol{\Delta} \leftarrow$ zeros$(N_{seg}, \text{length}(k_{idx}))$
for $e \leftarrow 1$ to N_{seg} **do**
  $\mathbf{p}^e \leftarrow$ find$(k_{idx} = e)$, $n_e \leftarrow$ length$(\mathbf{p}^e)$
  for $j \leftarrow 1$ to n_e **do**
    $(\delta_e)^T_{(\mathbf{p}^e)_j} = \frac{1}{n_e}$ ▷ Update each row of $\boldsymbol{\Delta}$
  end for
end for

Algorithm 2 Data Clustering

Require: $\bar{\mathbf{F}} \in \mathbb{R}^{N_{seg} \times L}$, $\boldsymbol{\Delta}$ downsampling matrix, κ clusters
Ensure: Segmentation of the spectral pixels: $\mathbf{F}_1, \cdots, \mathbf{F}_k$
  $\mathbf{G} \leftarrow$ Build_Sim_Graph$(\bar{\mathbf{F}})$ ▷ κ-nearest neighbor graph ▷ Obtain Cluster indices
  $\bar{\mathbf{C}}_{idx} \leftarrow$ Spectral_Clustering$(\mathbf{G}, \kappa)$▷ Spectral Clustering [18]
  $\mathbf{C}_{idx} \leftarrow \boldsymbol{\Delta}^T\bar{\mathbf{C}}_{idx}$ ▷ Upsampling

all the new segments are square and spatially homogeneous. Then, the $\mathbf{p}^e$ vectors are built for each segment e, and the new $\boldsymbol{\Delta}$ matrix is obtained using (3) (see Algorithm 1). Once the compressed measurements are acquired, the feature vector $\bar{\mathbf{f}}_l$ is obtained for each spectral band l, hence the feature matrix $\bar{\mathbf{F}}$ is constructed as $\bar{\mathbf{F}} = [\bar{\mathbf{f}}_1, \cdots, \bar{\mathbf{f}}_L] \in \mathbb{R}^{N_{seg} \times L}$, where the rows contain the average spectral information of each segment. **Data Clustering:** At each iteration of the main algorithm, the downsampling matrix $\boldsymbol{\Delta}$ is constructed, and it is used to obtain a partial clustering of the pixels using a subspace clustering method. Since, at each iteration it, the number of segments N_{seg} is increased, this approach can be seen as a multi-scale clustering of pixels. Furthermore, denoting N_s as the number of scales or levels in the hierarchy, the compression ratio given by using the SPC architecture and the proposed clustering approach can be determined as $\tilde{\gamma} = \frac{1}{MN}\sum_{it=1}^{N_s} N_{seg}^{(it)}$.

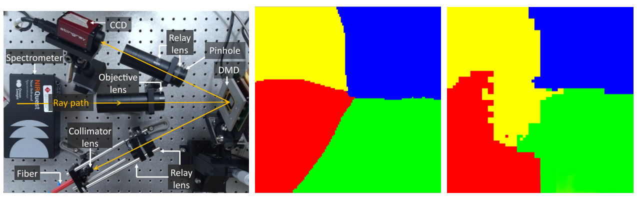
In order to perform the data clustering, we construct the similarity graph $\mathbf{G} \in \mathbb{R}^{n \times n}$ using the κ-nearest neighbor approach described in [18]. Then, the cluster indices $\bar{\mathbf{C}}$ are obtained by applying the spectral clustering to the similarity graph. Finally, the cluster membership of all the spectral pixels in the full image are obtained by applying the upsampling operator $\boldsymbol{\Delta}^T$ onto $\bar{\mathbf{C}}$, see Algorithm 2. Note that both, the similarity graph construction and the spectral clustering computation are performed on the feature matrix $\bar{\mathbf{F}}$. Hence, the computational performance of the proposed method improves over other traditional approaches.

4. Simulations results

In this section, the proposed hierarchical compressed subspace clustering method for SPC measurements is tested

Table 1. Quantitative results of different clustering approaches for the Indian Pines and University of Pavia real datasets. FMR [9]+SC and SPC-HSC [10] acquire SPC measurements from the near-infrared (NIR) and visible (VIS) spectrum, while the others only use the information from the NIR.

Dataset	Class	FMR [9]+SC	SPC-HSC [10]	N-CHSI + SC	Fast Recon.+SC, OA:	H2SPCI-SC (ours)	H2SPCI-SSC (ours)
Indian P.	AA	33.00	31.35	35.66	32.55	44.38	54.36
	OA	35.76	40.86	33.32	37.08	51.96	53.16
	Kappa	0.28	0.32	0.26	0.31	0.47	0.48
	Time [s]	37.31	10.91	74.30	28.29	2.66	13.29
U. Pavia	AA	46.53	57.01	57.28	46.88	52.53	56.67
	OA	43.86	65.35	64.92	51.30	53.28	64.08
	Kappa	0.36	0.57	0.58	0.42	0.45	0.58
	Time [s]	199.69	67.81	5352.61	1181.82	53.66	913.39



(a) (b) (c)

Figure 1. (a) Sketch of the Single-pixel imaging experimental setup. (b) Map ground truth. (c) Classification result via majority voting with $OA = 85\%$.

on two real remote sensing hyperspectral datasets: The **Indian Pines** image was acquired on the Northwestern Indian Pines test site. We crop the Indian Pines to have 128×128 spatial pixels, and 200 spectral bands and contains 16 land-cover classes [20]. The **University of Pavia** image was acquired over Pavia, Northern Italy. We crop the University of Pavia image to have 512×192 spatial pixels and 9 land-cover clases. Numerical results of the evaluated methods are presented in Table 1, we shown the average accuracy (AA), overall accuracy (OA), and Kappa coefficients. Notice that for the Indian Pines dataset, the best OA is achieved by the proposed strategy in this paper, using the "SSC" algorithm.

5. Experimental validation

We built a testbed in our laboratory to demonstrate the validity of the proposed ideas, through a proof-of-concept prototype, as shown in Fig. 1 (a). To demonstrate the proposed methodology classification capability, we conducted experimental validations using one composed target. This target is composed of four white materials: milk powder, sugar, bicarbonate, and salt. Using this scene, we aim to explicitly show the importance of considering the NIR for classification as pixels of this scene are very challenging to discriminate using only the information from the visible spectrum (VIS). For five hierarchical iterations with $N_{seg} = \{4^2, 8^2, 16^2, 32^2, 64^2\}$ the resulting compressive measurement exhibited $512 \times N_{seg}$ spectrometer pixels in size. The coded apertures patterns projected by the DMD were generated via Eq. (2) with a Hadamard matrix size of $\mathbf{W} \in \mathbb{R}^{N_x N_y \times N_x N_y}$ and $\mathbf{H}^{N_{seg} \times N_x N_y}$ where $N_x = N_y = 128$. Since the resulting matrix $\mathbf{H}$ is composed of $\{-1, 1\}$ values and it is not feasible to load negative values in the DMD [9], the sensing process is carried out by changing the -1's values for 0's. Then resulting binary pattern and a complementary version (i.e., changing 1's to 0's and 0's to 1's) of it are projected on the DMD. Finally, the acquired two measurements per pattern are reduced to $y_{10} - y_{01}$ in post-processing, i.e., y_{10} and y_{01} refers to the SPC measurement generated from the binary and complementary versions.

Figure 1 shows (b) the ground truth map and (c) the corresponding clustering map obtained by our method. These results were achieved by exploiting the NIR information preserved in the compressed measurements. The higher classification accuracy was achieved for $N_{seg} = 16^2$ (8×8 segment size), and the lower one was achieved for $N_{seg} = 64^2$ (2×2 segmente size). Since the pattern's pixel size proportionally increases with the regular decimation pixel size, the acquired SPC measurements are more robust to noise artifacts, a critical consideration in infrared experiments. Here the classification accuracy obtained using $N_{seg} = 8^2$ is deliberately set aside because it is assumed as an outlier.

6. Conclusions

This work presented a sensing matrix designed to extract features directly from the compressed measurements in each stage of the hierarchical model. We demonstrate that the proposed imaging system, together with the sensing protocol and the computational algorithm, represents an efficient alternative to estimate clustering maps without relying on oversampling sensing protocols. This paper showed extensive results on simulations and experimental proof-of-concept implementation. These results demonstrated that creating the final segmentation map through the majority voting method in the partial clustering results at each hierarchy step with the sensing matrices designed, achieves competitive results against other state-of-the-art methods. The main contribution presented in this document is the alternative to spectral clustering in CSI measurements only using the NIR spectrum and excluding the information from the traditional visible range.

References

[1] Gonzalo R Arce, David J Brady, Lawrence Carin, Henry Arguello, and David S Kittle. Compressive coded aperture spectral imaging: An introduction. *IEEE Signal Processing Magazine*, 31(1):105–115, 2013. 1

[2] Kevin Arias, Edwin Vargas, and Henry Arguello. Hyperspectral and multispectral image fusion based on a non-locally centralized sparse model and adaptive spatial-spectral dictionaries. In *2019 27th European Signal Processing Conference (EUSIPCO)*, pages 1–5. IEEE, 2019. 1

[3] Amir Beck and Marc Teboulle. A fast iterative shrinkage-thresholding algorithm for linear inverse problems. *SIAM journal on imaging sciences*, 2(1):183–202, 2009. 1

[4] Claudia V. Correa, Carlos Hinojosa, Gonzalo R. Arce, and Henry Arguello. Multiple snapshot colored compressive spectral imager. *Optical Engineering*, 56(4):041309, 2016. 1

[5] Marco F Duarte, Mark A Davenport, Dharmpal Takhar, Jason N Laska, Ting Sun, Kevin F Kelly, and Richard G Baraniuk. Single-pixel imaging via compressive sampling. *IEEE signal processing magazine*, 25(2):83–91, 2008. 1

[6] Mathieu Fauvel, Yuliya Tarabalka, Jon Atli Benediktsson, Jocelyn Chanussot, and James C Tilton. Advances in spectral-spatial classification of hyperspectral images. *Proceedings of the IEEE*, 101(3):652–675, 2012. 1

[7] Mário AT Figueiredo, Robert D Nowak, and Stephen J Wright. Gradient projection for sparse reconstruction: Application to compressed sensing and other inverse problems. *IEEE Journal of selected topics in signal processing*, 1(4):586–597, 2007. 1

[8] H. Garcia, C. V. Correa, and H. Arguello. Multi-resolution compressive spectral imaging reconstruction from single pixel measurements. *IEEE Transactions on Image Processing*, 27(12):6174–6184, Dec 2018. 2

[9] Hans Garcia, Claudia V Correa, Karen Sánchez, Edwin Vargas, and Henry Arguello. Multi-resolution coded apertures based on side information for single pixel spectral reconstruction. In *2018 26th European Signal Processing Conference (EUSIPCO)*, pages 2215–2219. IEEE, 2018. 3

[10] Carlos Hinojosa, Jorge Bacca, Edwin Vargas, Sergio Castillo, and Henry Arguello. Single-pixel camera sensing matrix design for hierarchical compressed spectral clustering. In *2019 IEEE 29th International Workshop on Machine Learning for Signal Processing (MLSP)*, pages 1–6. IEEE, 2019. 1, 3

[11] Carlos Hinojosa, Karen Sanchez, Hans Garcia, and Henry Arguello. C-3spcd: coded aperture similarity constrained design for spatio-spectral classification of single-pixel measurements. *Applied Optics*, 61(8):E21–E32, 2022. 1

[12] Carlos A Hinojosa, Fernando Rojas, Sergio Castillo, and Henry Arguello. Hyperspectral image segmentation using 3d regularized subspace clustering model. *Journal of Applied Remote Sensing*, 15(1):016508, 2021. 1

[13] Jhon Lopez, Carlos A Hinojosa, and Henry Arguello. Efficient subspace clustering of hyperspectral images using similarity-constrained sampling. *Journal of Applied Remote Sensing*, 15(3):036507, 2021. 1

[14] Jonathan Monsalve, Miguel Marquez, Iñaki Esnaola, and Henry Arguello. Compressive covariance matrix estimation from a dual-dispersive coded aperture spectral imager. In *2021 IEEE International Conference on Image Processing (ICIP)*, pages 2823–2827. IEEE, 2021. 1

[15] Jonathan Monsalve, Juan Ramirez, Iñaki Esnaola, and Henry Arguello. Covariance Estimation from Compressive Data Partitions using a Projected Gradient-based Algorithm. *arXiv:2101.04027*, pages 1–10, jan 2022. 1

[16] Karen Sanchez, Carlos Hinojosa, and Henry Arguello. Supervised spatio-spectral classification of fused images using superpixels. *Applied optics*, 58(7):B9–B18, 2019. 1

[17] Aswin C Sankaranarayanan, Lina Xu, Christoph Studer, Yun Li, Kevin F Kelly, and Richard G Baraniuk. Video compressive sensing for spatial multiplexing cameras using motion-flow models. *SIAM Journal on Imaging Sciences*, 8(3):1489–1518, 2015. 2

[18] Ulrike Von Luxburg. A tutorial on spectral clustering. *Statistics and computing*, 17(4):395–416, 2007. 2

[19] Li Wang, Yan Feng, Yanlong Gao, Zhongliang Wang, and Mingyi He. Compressed sensing reconstruction of hyperspectral images based on spectral unmixing. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 11(4):1266–1284, 2018. 1

[20] Hongyan Zhang, Han Zhai, Liangpei Zhang, and Pingxiang Li. Spectral–spatial sparse subspace clustering for hyperspectral remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, 54(6):3672–3684, 2016. 3