SPARSITY BASED SPECTRAL SUPER-RESOLUTION AND APPLICATIONS TO OCEAN WATER COLOR

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INTRODUCTION AND BACKGROUND

Hyperspectral imagery (HSI) is an important imaging modality for remote sensing applications in many fields, including oceanic and atmospheric sciences [1], agriculture [2], defense, and space exploration [3]. Despite the richer potential of HSI sensors for scientific studies and applications, engineering tradeoffs, such as memory and communication bandwidth constraints, typically favor multispectral (MSI) sensor designs. We outline here continuing work which utilizes the statistical structure of HSI in order to extrapolate HSI-resolution spectra from more limited multi-spectral measurements. Accurate spectral super-resolution can substantially extend the utility of current and legacy MSI sensors, as well as open up the engineering design space of future missions. Ideally, both high spatial and high spectral resolution can be obtained with a combination of heritage optical design and sparse signal processing. While previous works on this topic demonstrate success on resolving MSI data simulated by artificially blurring real HSI images [4, 5], we demonstrate the utility of our methods on resolving real MSI data and validating the results by comparing to HSI images of the same scene. Specifically, we take geographically co-located oceanic water-color images taken by the VIIRS MSI imager [6] and the HICO HSI imager [7] and demonstrate that the proposed methodology can extrapolate HICO-resolution spectra from the more limited VIIRS measurements.

Our proposed methodology is based on recent advances in sparsity-based signal processing. Sparsity-based techniques seek to describe data via a parsimonious representation in a large ambient space. In particular, given a large dictionary of feature vectors, sparse methods attempt to recover the smallest number of these features which explain the observation. Sparsity-based signal processing has proven invaluable in obtaining state-of-the-art solution to many linear inverse problems [8], and recent work demonstrates the applicability of sparsity based methods to HSI data. In fact both spatial and spectral sparsity has been used in the HSI literature for spectral unmixing [9, 10], classification [11], spectral dictionary learning [12, 4], and spatial super-resolution [13].

SPECTRAL SUPER-RESOLUTION

In this work we address super-resolution in the spectral domain rather than more typical spatial super resolution, hence we leverage the spectral sparsity of HSI. In particular, we use a linear mixing model to define the measured spectrum $\boldsymbol{x}_{i,k}$ at each pixel $\{i,k\}$ as a sum of weighted 'pure' material spectra $\boldsymbol{\phi}_n$,

$$\boldsymbol{x}_{i,k} = \sum_{n=1}^{N} \boldsymbol{\phi}_n a_{i,k,n} + \boldsymbol{\epsilon}_{i,k}, \tag{1}$$

where the weights $a_{i,k,n}$ represent how strongly the n^{th} material is present in the $\{i,k\}^{th}$ pixel and $\boldsymbol{\epsilon}_{i,k}$ represents potential sensor noise at each pixel. Under this model, we can conclude that for fine enough spatial resolutions, it is sensible to assume that only a few materials are present in any given pixel. This essentially assumes a sparsity model on $a_{i,j,n}$ which can be used to uncover the material contributions in the *spectral unmixing* problem. The dictionary of material signatures $\boldsymbol{\phi}_n$ are typically assumed known, however a number of techniques exist to extract these signatures from exemplar HSI data.

In the spectral super-resolution problem, we seek to go beyond unmixing. Instead of the full spectrum, we instead assume that we only obtain few, coarser measurements that span only a portion of the total desired spectrum. These measurements are essentially multi-spectral images. We can concisely write the coarse measured spectra as

$$\boldsymbol{y}_{i,k} = \boldsymbol{B}\boldsymbol{x}_{i,k} = \sum_{n=1}^{N} \boldsymbol{B}\boldsymbol{\phi}_n a_{i,k,n} + \widetilde{\boldsymbol{\epsilon}}_{i,k}, \tag{2}$$

where $\boldsymbol{B}$ is a 'blurring' matrix that represents how the measured spectra are related to the desired HSI spectra and $\widetilde{\boldsymbol{\epsilon}}_{i,k}$ represents the measurement noise of the new measurement process. The blurring operator $\boldsymbol{B}$ can be considered as an operator that either merges neighboring spectral bands together (i.e. a blurring operator) or omits bands completely. To achieve our goal of inverting this highly undetermined linear operator and recovering the HSI-resolution spectra, we focus on first recovering the sparse mixture coefficients via a regularized least-squares optimization, and then using those coefficients with a known dictionary of material spectra to recover the high-resolution spectra.

More recent results increase the effectiveness of this procedure by accounting for inter-signal dependencies via spatial filtering. Instead of treating the super-resolution of each spectra as a separate problem, the knowledge that neighboring pixels are likely composed of similar materials is used in conjunction with the sparsity information to obtain more accurate results.

OCEAN COLOR: VIIRS TO HICO

While our previous work has relied on creating simulated MSI measurements from HSI images to test our sparsity-based super resolution techniques, we present here results using geographically co-located images of oceanic water-color. Specifically, we take two images (one taken with the 89-channel HICO sensor and one taken with the 5-channel VIIRS sensor), and resolve the VIIRS spectra to HICO-resolution spectra.

To perform our super-resolution we first learn a dictionary of material spectra via the techniques outlined in [4]. Next we estimate the blurring operator by comparing the relative signal-to-noise ratios for both the VIIRS and HICO sensors over their respective spectral ranges, which allows us to super-resolve the VIIRS data using our sparsity-based methodology. We validate our super-resolved VIIRS spectra by comparing to high-resolution measurements from the HICO sensor. Figure 1 shows some example recovered spectra. In particular, the most accurate, least accurate and median (typical) recovery, as based on the spectral angle between the recovered spectra and the HICO spectra at the same geographical coordinates, are all shown. With a median spectral angle of 7.43 degrees, we note that the recovered spectra accurately represent the HICO spectra. Additionally, we study where and how the super-resolution does not match the HICO data. For example, the best matches occurred over water pixels, while the worst matches occurred along the shore. One potential source of this shoreline discrepancy is that along the shore there are typically more materials present, indicating a model mismatch with the sparsity assumption. Another potential source of the mismatch is that although the VIIRS and HICO images were acquired at the same geographical location and at the same date, the images were taken approximately 8 hours apart, indicating that tidal changes may have actually changed the shoreline composition from water spectra to land spectra.

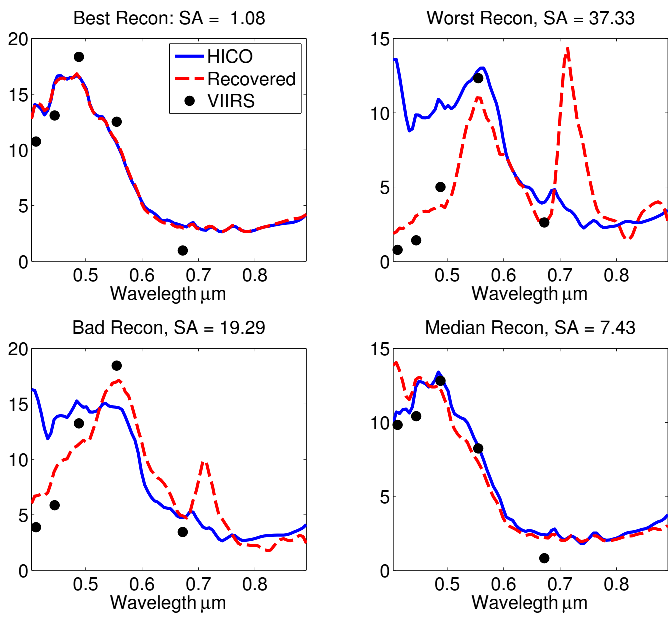

Fig. 1. Examples of spectral super-resolution of a VIIRS image taken around the Acqua Alta Oceanographic Tower (AAOT) near Venice, Italy on February 11, 2012. In each figure the black dots represent the five VIIRS measurements, the solid blue lines represent the HICO spectrum captured near that location, and the dashed red line represents the super-resolved VIIRS spectrum. Shown are examples of the best reconstruction (top left) the worst reconstruction (top right), bad reconstruction (bottom left) and median reconstruction (bottom right). As the median reconstruction was fairly accurate, we note that the majority of the super-resolved spectra (in particular water-color pixels) are recovered well.

Overall, our results indicate that sparsity-based spectral super-resolution techniques can greatly extend the utility of legacy MSI and HSI instruments via post-processing. Additionally, accurate super-resolution could impact future sensor designs by creating options for lighter sensors with reduced transmission bandwidth at the cost of additional computation at base stations.

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