Compressed Hyperspectral Sensing

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ABSTRACT

A fundamental problem that HyperSpectral Imaging sensors must address is how to collect the three dimensional HSI data, along the two spatial and the one spectral dimensions, using either a single, a 1D array, or a 2D array of detectors. The discrepancy between the required and the available dimensionality of detectors has sparked different philosophies in HSI acquisition system designs, each one with its own specific capabilities in terms of spatial, temporal, and spectral resolution. A key shortcoming shared by all current methods lies in the high scanning repetition rates required for generating the complete 3D hyperspectral datacube. In the case of spatial/spectral scanning, multiple lines/pixels have to be scanned, while for 2D frame scanning systems, multiple frames have to be acquired in order to obtain the complete spectral profile of the scene. This limitation is responsible for a number of issues that hinder HSI performance, including slow acquisition time and motion artifacts. To address these limitations, Snapshot (or Simultaneous) Spectral Imaging (SSI) systems[1] acquire the complete spatio-spectral cube from a single or a few captured frames, i.e., during a single or a few integration periods, without the need for successive frame acquisition.

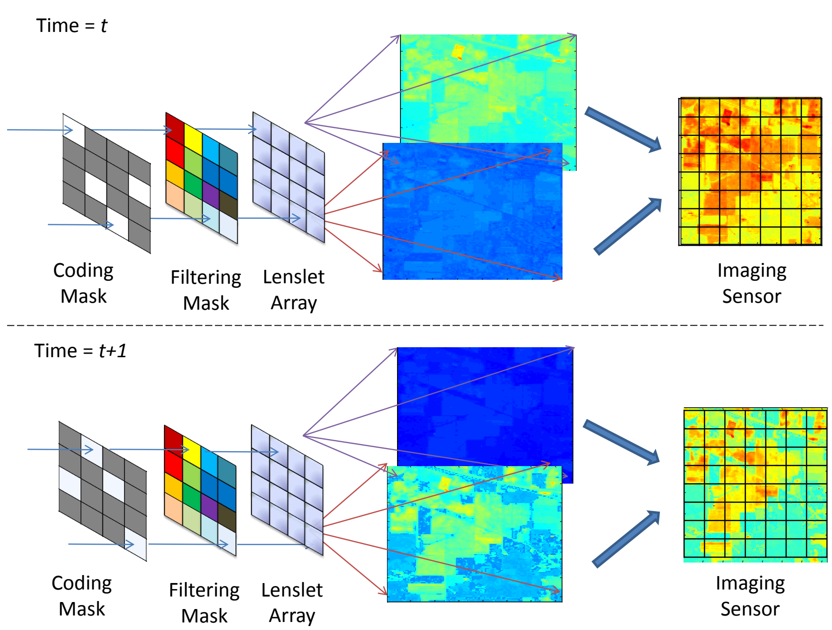

Figure 1: Image acquisition via the proposed scheme in two different sampling instances. During each sampling instance, the pattern of the coding mask allows the propagation of light from a specific spectral band which is optically multiplexed in the imaging sensor.

In this work, we proposed a novel HSI architecture that can achieve high quality reconstruction of the hypercube $\mathbf{I}(\mathbf{x}, \lambda)$ from a limited number of frames, without resorting to moving parts, by exploiting the theory

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of Compressed Sensing (CS).[2] According to the CS framework, perfect reconstruction of a signal $\mathbf{x} \in \mathbb{R}^N$ is possible from a small number of random measurements $\mathbf{y} \in \mathbb{R}^M$, far below the typical Shannon-Nyquist sampling limit, provided the signal $\mathbf{x}$ can be sparsely represented in a collection of elementary examples, $\mathbf{D}$, i.e., $\mathbf{x} = \mathbf{D}\mathbf{s}$.

Figure 1 illustrates both the schematic overview of the proposed architecture as well as the functional behavior over time. More specifically, the system is composed of the following elements: (i) a coding mask that can allow or block the incoming light according to a specific dynamically changing sampling pattern. Such a sampling mechanism can be implemented using a Digital Micromirror Device (DMD); (ii) an array of optical filters that filter the incoming light allowing only a specific set of spectral bands to propagate; and (iii) an array of lenses, also called a Lenslet array, that focus the filtered light onto the imaging sensor, such as a CCD or a CMOS device.

During each sampling instance, the imaging sensor captures light from the entire scene, however the recorded values correspond to a mixture of spectral bands, defined by the specific coding $\Psi(\mathbf{x}, t)$. To recover the spectral profile at location $\mathbf{x}$, we must solve the following minimization problem

$$\mathbf{s}^*(\mathbf{x}) = \arg\min \|\mathbf{s}(\mathbf{x})\|_0 + \lambda \|\hat{\mathbf{y}}(\mathbf{x}, t) - \mathbf{\Psi}(\mathbf{x}, t)\mathbf{D}\mathbf{s}(\mathbf{x})\|_2 \ . \tag{1}$$

Each hyperpixel can then be retrieved by $\mathbf{I}(\mathbf{x}, \lambda) = \mathbf{D}\mathbf{s}^*(\mathbf{x})$. Figure 2 showcases the recovery performance of HSI data using the proposed imaging architecture, where a binary sampling pattern of 10 active elements per frame and a dictionary consisting of 280 training hyperspectral profiles are employed. Traditional imaging with the proposed architecture would require the acquisition of 220 spectral frames. Clearly, a high quality reconstruction of the full hypercube is possible from a significantly smaller number of frames thanks to the proposed efficient encoding and decoding procedures.

REFERENCES

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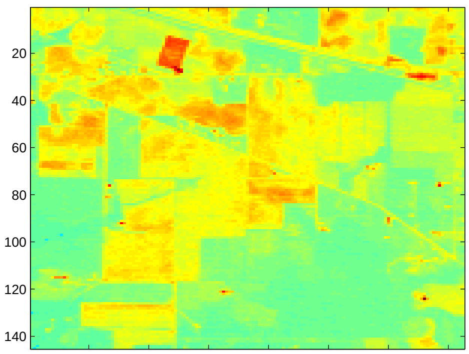
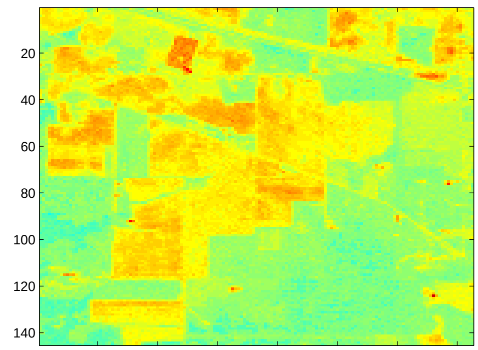
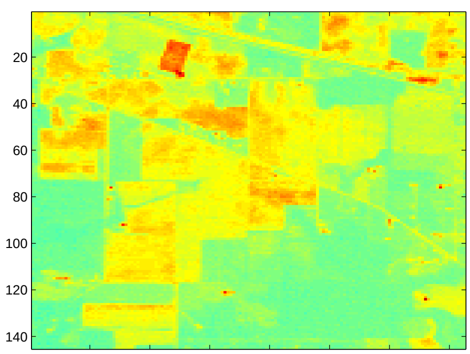
2. Donoho, D., "Compressed sensing," *Information Theory, IEEE Transactions on* **52**(4), 1289–1306 (2006).



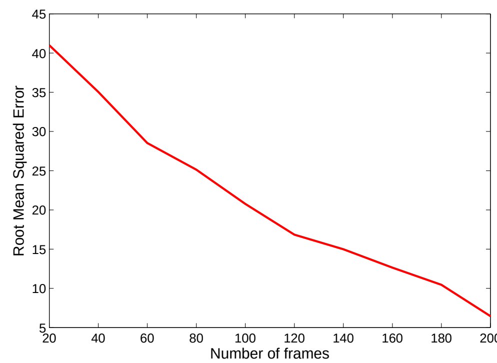
(a) 10^{th} spectral band from AVIRIS indian pines dataset



(b) Reconstruction from 10 multiplexed frames



(c) Reconstruction from 20 multiplexed frames



(d) Reconstruction error as a function of mulitplexed frames

Figure 2: Illustrative examples of the original image (a) and the reconstructed spectral images (b)-(c). The overall mean reconstruction error as a function of the number of frames is shown in (d).