Spectral Super-Resolution for Hyperspectral Images via Sparse Representations

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Over the last decade Hyperspectral Imaging (HSI) systems created an enormous outburst in the field of earth observation. Multiple instrument on-board imaging systems are currently available, providing a large amount of hyperspectral imagery for various applications, such as precision agriculture, geology and oceanography. Despite the important advantages hyperspectral imaging systems demonstrate, HSI acquisition and processing stages usually introduce multiple constraints. Slow acquisition time, limited spectral and spatial resolution, low dynamic range, and restricted field of view, are some of the limitations that hyperspectral sensors experience, and require further investigation.

Enhancing the spectral resolution, i.e., number of distinct spectral bands, of the acquired images is critical for both visualization and subsequent analysis, including spectral unmixing, pixel classification and region clustering. High spectral resolution imaging systems are able to capture a huge amount of data, including the 2D spatial and the 1D spectral variations of an input scene over time. Unfortunately, various factors can lead to the introduction of imaging constraints such as the case of Spectrally Resolvable Detector Arrays systems that directly acquire the entire 3D data-cube through a combination of spectral filters and detector elements. Despite the dramatic reduction these systems exhibit with respect to acquisition time, such designs also lead to a reduction of the spectral resolution by associating each pixel with a single spectral band.

In order to overcome the aforementioned limitations, we propose a novel spectral resolution enhancement framework of low spectral resolution imagery, based on the Sparse Representations (SR) framework. Unlike state-of-the-art hyperspectral super-resolution methods that utilize inherent correlations to obtain high spatial resolution images, the proposed algorithm aims at enhancing the spectral content of the imagery. This goal is achieved by introducing the assumption that each high spectral resolution “hyper-pixel” can be estimated from its low resolution version by identifying a sparse representation encoding that directly generates the high-spectral resolution output.

The notion of sparsity has revolutionized modern signal processing and machine learning, and has lead to very impressive results in a variety of imaging problems, including deblurring, denoising, etc. In this work, we enforce the sparsity constraint through learning a joint sparse coding dictionary from multiple low and high spectral resolution training image pairs. To the best of our knowledge, this is the first work that proposes a spectral super-resolution technique for hyperspectral images. A crucial requirement for the recovery process is the proper generation of the two dictionaries, in order to simultaneously sparsify the low and high resolution hyperspectral data. The joint learning of the two dictionaries encodes the assumption that both the high and the low spectral resolution hyperspectral pixels can share the same sparse code, since they adhere to similar statistical characteristics under different spectral-resolution conditions. For this purpose, multiple pixels are sampled from large collections of high and their correspondent low spectral resolution training hyperspectral images.

Early experiments were conducted on images acquired by NASA’s Hyperion hyperspectral instrument, where we extracted a limited number of spectral bands, and successfully recovered the full spectral resolution of the instrument. Furthermore, our spectral resolution enhancement scheme can also be applied to HSI data acquired by other instruments, containing limited spectral information, such as Sentinel’s 2 multispectral instrument. The proposed enhanced spectral bands can
be compared with the ground truth, properly aligned Hyperion’s spectral bands. The proposed system’s block diagram is overviewed in fig.1, where we recover the high spectral resolution version of a low spectral resolution input scene, acquired by the Hyperion instrument. In this experiment we consider 15 spectral bands for the input low-spectral resolution image, and efficiently reconstructed 39 high-spectral resolution bands. However, our system is able to handle larger spectral resolution up-scaling factors.

**Fig.1:** Overall system’s block diagram: Given a low-spectral resolution hyperspectral image, acquired with 15 spectral bands, the proposed algorithm represents the input “hyper-pixels” as sparse linear combinations of atoms extracted by a proper dictionary matrix $D_1 \in \mathbb{R}^{15 \times 512}$, created by relative 15 spectral-bands pixels. The sparse coefficients are directly mapped to the high-spectral resolution dictionary, generated by correspondent high-spectral resolution pixels, of 39 spectral-bands. The resulting “hyper-pixels” represent the whole spectral information and are properly combined to generate the full 3D data-cube.

The proposed inverse spectral resolution enhancement problem recovers high spectral information, capitalizing on the sparse representations framework as prior-knowledge, effectively encoding the relationships between high and low spectral representations. Additionally, the proposed scheme can be extended to handle large ranges of low-to-high resolution enhancements by efficient modifications of the joint dictionary learning process, as well as offering the capability of addressing additional sources of HSI image degradation such as blurring and noise.

**References**