Chapter 7

Conclusions

This thesis focused on four related problems in multi-dimensional imaging namely multispectral demosaicing, hyperspectral denoising, hyperspectral unmixing, and hyperspectral classification. These are classical imaging problems that have been addressed in literature from different perspectives. This work has attempted to model them as compressed sensing and sparse recovery related problems.

The multispectral demosaicing problem is an extension of the color demosaicing problem that occurs in design of low cost and small size multi-spectral cameras. As there is no standard multispectral filter array to capture multiple bands, therefore, we proposed a uniform multispectral filter array such that minimum changes are required in the design of color imaging cameras to capture multispectral images. The focus of this work on multispectral imaging problem was on the reconstruction algorithm to create the full image from the raw image. When five bands are captured using a single-sensor then there are only 20% samples of each band in the raw image; therefore, reconstruction of the full image become very challenging. The single sensor based design is dependent on cheap silicon technology that can be used to capture images in the wavelength range of around 1100 nm.

Quantitative results proved that reconstruction quality of proposed multispectral demosaicing approach is better than the already existing algorithm used in the comparative study. Currently, experiments have been performed with three to six-band multispectral images and more experiments need to be carried out by increasing the number of bands and by varying spectral gap. Once offline training is completed, then the proposed algorithm is linear-time because every pixel is visited only once for doing interpolation. It is desirable to extend the current technique such that it does not depend on training data. This technique is limited to hand-held multispectral cameras and not readily extendable for push-broom or whisk-broom kind of multispectral imaging sensors. Further, there are pseudo-random and panchromatic filter array designs to capture multispectral image therefore, a comparative study with uniform filter array can be carried out.

The second problem discussed in the thesis is the hyperspectral denoising problem. Hyperspectral denoising is an important pre-processing step in many applications of these images such as classification, change detection, data fusion, etc.. Initially, we addressed the problem of reducing impulse noise followed by mixed noise reduction problem. There have been studies to remove impulse noise from grayscale images
and also Gaussian noise from hyperspectral images but little work on reducing impulse noise from hyperspectral images. The problem has been formulated both as a synthesis prior and an analysis prior form. Since impulse noise corrupt few pixels in the image, therefore, this noise has been modeled as sparse noise. Thus, our proposed formulation leads to $\ell_1$-norm regularized $\ell_1$-norm data fidelity minimization problem. We use two dictionaries to de-correlate hyperspectral datacube in both spatial and spectral dimensions that result in a very sparse representation.

The problem formulation considers a general noise model that explicitly accounts for not only Gaussian noise but also sparse noise. The inherent structure of hyperspectral images has been explored in the analysis prior case by utilizing 2D total-variation along spatial dimension and 1D total-variation along the spectral dimension. The synthesis prior approach utilized DCT along both spatial and spectral dimension. The denoising problem was formulated as an optimization problem whose solution has been derived using split-Bregman approach. Experiments were carried out using synthetic as well as real noise hyperspectral images. Synthetic noise experiments were performed to quantify the denoising strength of proposed technique using PSNR and SSIM. The quantitative and qualitative results demonstrate that proposed algorithm reduce a significant amount of noise from real noisy hyperspectral images compared to existing state of the art approaches.

The proposed denoising algorithm is applied to all the bands. This work did not look at the problem of identifying noise corrupted bands and applying denoising algorithm on the selected number of bands. This work assumed the impulse noise as additive noise and did not try to recognize the impulse noise corrupted pixels explicitly as done in some existing algorithms.

The third problem considered in this thesis is the unmixing problem, we have proposed a new approach for hyperspectral unmixing. This approach does not depend on the pure pixel assumption. We also relaxed the abundance sum-to-one constraint. This method exploits joint sparsity as well as the piecewise smoothness of abundance maps in the generic noise model which explicitly account for sparse noise. Experimental results suggest the advantage of proposed method over existing methods. Simultaneous utilization of both total-variation regularization and joint-sparse regularization is not redundant as both achieve different goals. Total variation regularization has explored smoothness of abundance maps whereas joint-sparsity exploit the fact that an endmember if present, shall be present at various locations in the same area.

This work utilized existing USGS spectral library for spectral signatures. The spectral signatures in the existing library can differ from the spectral signatures present in the image. Also, it is possible that real images have endmembers whose spectral signatures are not present in existing libraries; therefore, it is desirable to derive the endmember signatures directly from the hyperspectral image.

A new paradigm for deep learning called ‘deep dictionary learning’ was introduced for hyperspectral classification. The learning proceeds in a greedy fashion. In the first stage, a dictionary and the corresponding representation are learned from the input training samples. In the second layer, the representation from the first layer acts
as an input, and the second level of dictionary and representation are learned. The same process is continued for training deeper levels. The advantage of the greedy approach is twofold. First, it prevents over-fitting, since we do not need to train all the layers simultaneously. Second, the alternating minimization technique used for learning each layer of training enjoys certain convergence guarantees. In this preliminary work, the proposed technique was compared with two standard deep learning tools - deep belief network and stacked autoencoder. In the future, we will try to improve further by pre-processing the input. Our proposed method is unsupervised. There is a plethora of work in supervised dictionary learning for computer vision problems. In future, we would like to extend our work on robust dictionary learning to incorporate supervised dictionary learning penalties.

Source codes for multispectral demosaicing [123], hyperspectral denoising [124], and unmixing [125] are made available to promote reproducible research.