Chapter 1

Introduction

Imaging is the science and engineering of developing hardware and software solutions to capture light energy. Every object on earth can absorb, reflect and transmit some amount of radiations at certain wavelengths of electromagnetic spectrum depending on the properties of that object. This light energy coming from an object can be captured and processed using various imaging technologies. The captured light energy can be further processed, visualized, and analyzed depending on the application. This chapter describes what multidimensional images are, how to capture them, which specific imaging problems are discussed in this dissertation and what are specific research contributions.

1.1 Background

Image processing is active interdisciplinary research area at the intersection of various fields such as signal processing, optimization, computer science, calculus, and probability. Image processing acts as a building block for subjects like pattern recognition, computer vision, video processing. Image processing is ubiquitous as it has applications in geology, astrophysics, geography, military services, medicine, biology, remote sensing, environmental science, etc..

Images captured in more than one band of the electromagnetic spectrum are termed as multidimensional images. These multiband images can be thought of as a collection of the gray-scale images of a particular object taken at different wavelengths in parallel. Images can be captured at different wavelength regions depending on the application areas such as X-ray images, ultra-violet images, radar images, thermal images, color images, panchromatic images, etc. This work focuses on multidimensional images that are captured from near ultraviolet to infrared region between the wavelength range of around 400 nm to 2500 nm. A multispectral image has three to thirty bands whereas hyperspectral images have hundreds of bands with a very narrow spectral gap. Figure 1.1 shows a sample color image of 3 bands, a multispectral image with five bands, a hyperspectral image with 360 bands.

There are applications that benefits by capturing some wavelengths of light outside the visible region. Multispectral images have been successfully used in the detection of oil spill on the sea surface [4, 5] using both active and passive remote sensing tech-
The infrared images help to tackle the impact of illumination changes in the face recognition problem [6–8]. Hyperspectral images are also used for imaging in the ultraviolet range which is challenging due to high scattering of light in below visible range. The applications include detection of colored dissolved organic matter in natural water. UV light is used in many applications such as small amount of surface contamination, scratches on the lenses, criminology, etc. Crop monitoring is an important application of remote sensing images [9, 10] in agriculture domain. Crop monitoring includes crop production, monitoring, checking for diseases, and soil moisture detection. Satellite images are extensively used in geological applications such as mineral exploration [11] application, underwater exploration, buried sediments analysis, etc.. A review of various applications of hyperspectral images in medicine domain can be found in [12]. Hyperspectral images are used in applications such as tumor identification, making surgical decisions, evaluating the health of dental structures etc.. Remote sensing images assist in planning of resource management, landscape management [13], monitoring the condition of habitats and species distribution.

Sparse Recovery

A signal is said to be sparse if it contains very few nonzero coefficients compared to its length. Similarly, a signal is said to be compressible if the absolute value of its sorted coefficients follows a power law decay. Figure 1.2 shows an example of the compressible representation of a hyperspectral image. Figure 1.2(a) shows the sparse representation of band 10 of WDC image of size 256 × 256 by using two-dimensional Discrete Cosine Transform (DCT). It can be observed that coefficient values decay exponentially and only around 100 out of a total of 65536 coefficients are significant. The image is compressible because of the existence of high spatial correlation among neighboring pixel values.

The image is compressible not only spatially but also spectrally. In a hyperspectral image, each pixel is captured over hundreds of bands having very narrow spectral gap; therefore, each pixel is spectrally correlated as well. Figure 1.2(b) shows the plot of sorted one-dimensional DCT coefficients for some pixels of WDC image over 191 bands. It can be observed that there are around ten significant coefficients compared to 191.
Figure 1.2: Spatial and spectral compressibility of hyperspectral images

1.2 Multispectral Demosaicing

The term imaging refers to the process of capturing, processing, analyzing, and visualizing an image. Imaging is a very broad and active research area and this dissertation particularly focuses on three imaging problems namely multispectral demosaicing problem, hyperspectral denoising problem, and hyperspectral unmixing problem. Figure 1.3 shows the process of capturing a color image using single-sensor architecture.

Figure 1.3: Color imaging process using single-sensor architecture.

When light enters through the lens of a point and shoot digital camera then initially there is a shutter inside it that allows light to enter inside the camera. If the shutter is open for a long time, then more light enters in the camera. After that, there is an infrared cutter that does not allow infrared light to penetrate into the camera. Followed
by the infrared cutter, there is an optical low pass filter that allows only the light with low frequency to enter because high-frequency light has high energy and can damage the hardware of the camera. Hence, both, very low and very high wavelengths are stopped to enter into the camera. The optical low pass filter is followed by a micro-lens array that focuses the incoming light onto the color filter array which allows a particular wavelength to hit a photo-diode on the image sensor. When the energy of incoming light photons is higher than that of band-gap energy of semiconductor (silicon), then the electron-hole pair is generated. These electrons generated inside the depletion region are utilized as signal charge. This electron charge is converted into the voltage by an active transistor inside the pixel.

Color imaging using a single sensor is possible because of the invention of Color Filter Array (CFA) that filters the light such that only one particular wavelength is captured at a pixel. The most popular CFA is Bayer filter [14] that capture 50% samples of green band and 25% samples for each of red and blue band. The green band is captured twice that of red and blue because our eyes are more sensitive to green band compared to the other two. Thus, at each pixel, only a single color intensity is captured such an image is termed as the raw image. This image is also called mosaiced image because it is a combination of three bands. The raw image has only one value at each pixel and remaining two have to be interpolated for each pixel. This process of interpolating the unknown pixel values is called color image demosaicing problem. There are many linear and non-linear demosaicing algorithms to reconstruct the full-color image from the raw image. This work extends the single-sensor color imaging architecture to multispectral imaging architecture.

There has been a lot of advancement in the various aspects of camera technology such as reduction in camera size, higher image resolution, more efficient imaging sensors, fast image processing algorithms, etc. Due to these advancements, the color imaging technology has become very popular in different application areas. Despite having more information content than color images, multispectral imaging is not widely used because they are not as accessible as color images due to the high cost of multispectral cameras. The main cause of high cost of such cameras is the use of several expensive imaging sensors and many moving optical and mechanical parts.

Many multi-spectral cameras have as many CCD-sensors as the number of bands to be captured. An example of a multispectral camera is shown in Fig. 1.4. This camera has six imaging sensors to capture six different wavelengths of light by using different filters. The size and cost of multi-spectral cameras increases with the number of CCD sensors required to capture a larger number of bands of electromagnetic spectrum. The main motivation of this work is to bring down the cost of the multi-spectral cameras by proposing a single-sensor architecture as used for color image acquisition. The use of multiple image sensors causes complexities such as pixel-to-pixel registration of each band so that all the imaging sensors capture same area as accurately as possible. Furthermore, multi-sensor cameras consume more power to operate due to complex circuitry as compared to single-sensor cameras. Therefore, it is desirable to have a single-sensor multi-spectral camera that can handle above mentioned limitations to a certain extent.
There is a vast literature on CFA and the corresponding demosaicing algorithms. Many single-sensor digital cameras capture color images using Bayer pattern [14] where 50% samples of green band and 25% each of red and the blue band are obtained. Many linear and non-linear demosaicing algorithms have been proposed in the literature for finding missing intensity values at each pixel. A review of color image demosaicing algorithms is mentioned in [15]. Linear time gradient-based bilinear interpolation technique have been proposed in [16] where it has been claimed to be superior to many non-linear algorithms. The design idea of Bayer pattern and many such algorithms is based on the property of the human visual system that human eye is more sensitive to the green band as compare to the red and blue band. The idea of Bayer pattern may not be directly generalized to develop filters and demosaicing algorithms for multi-spectral images since there are large number of bands each having some unique characteristics.

A multispectral filter array design have been proposed in [17] which is based on the probability of appearance of each band to be used in target recognition. This design takes into account spectral consistency which is used to avoid optical cross-talk that causes some artifacts into the image. Authors of that paper also considered spatial uniformity which says that for doing interpolation, uniform sampling is better than random sampling. This filter design is a three step process consisting of finding binary tree based on the probability of appearance, determining pixel locations for interpolation using checkerboard selection, and finally combining the results to get the raw image. However, that proposed design of filter array is based on the prior knowledge of the probability of appearance of bands. Based on above filter array design, a generic demosaicing approach Binary Tree based Edge Sensing (BTES) algorithm has been proposed in [18] which is based on exploring edge correlation to do the interpolation of missing band values. That algorithm first determines which band to interpolate based on the probability of appearance of each band and then order of interpolation for each pixel is determined followed by image transforms to do the interpolation. A multi-spectral camera design has also been proposed in [19] which is based on extending color filter array design using color channel differences. This filter is a $3 \times 2$ multi-spectral filter on CCD-chip. Authors selected this design for doing fast bi-linear interpolation to find unknown intensity values. This technique is based...
spectral channel differences which can be considered as a smoothing operation after bi-linear interpolation. This algorithm does not make use of the spectral-correlation among bands of multi-spectral imagery.

Multispectral images are captured using a multi-sensor architecture that uses a separate sensor to capture each band. Since for each band, there is a separate sensor, therefore, the quality of acquired image is very high, and there is no need for image interpolation algorithm. Due to the use of numerous hardware and optical-mechanical parts, the size and cost of these imaging devices are very high. When several bands corresponding to the same scene are captured by different sensors, then there is the probability of error in the measurement process in the sense that individual pixels may not be corresponding to the same spatial location. This problem is often termed as the image to image registration problem.

This work aims at addressing the problem of reducing size and cost of hand-held multispectral cameras by utilizing single-sensor based architecture which is used in most compact digital cameras for color imaging.

The use of single-sensor can reduce the size and cost of the multispectral camera. It poses several challenges. There is no standard optical filter array to capture multiple bands using the single-sensor architecture similar to Bayer filter for color imaging. Bayer filter is not directly extensible for multi-spectral imaging because that has been designed according to the sensitivity of the human visual system. In the case of multispectral images, we shall not use the filters that have been designed for color images since we are trying to capture beyond visible range. Therefore, there is need of Multispectral Filter Array (MSFA) that allows us to take measurements of several bands. Let there exists some MSF array which allows capturing multispectral images using single-sensor then if we capture four bands then we will have only 25% samples, on the other hand, with five bands we will only have 20% samples of each band. Recovering a full image from such a small number of samples is a challenging problem. Figure 1.5 shows how to extend color imaging architecture for multispectral imaging.

Figure 1.5: Multispectral Demosaicing Process

A minimal change in the existing hardware has been proposed. In particular, the CFA need to be replaced with MSFA that will allow capturing multiple wavelengths of light. There are several challenges in achieving it such as the MSFA should be
generic enough to be adapted to different multispectral imaging requirements such as the number of bands and the spectral gap. The MSFA should not be dependent on the properties of the human visual system since multispectral imaging also spans invisible region.

After obtaining the raw multispectral image from MSFA, an interpolation algorithm is required to obtain the full multispectral image from the raw image as shown in Fig. 1.5. This work also focuses towards developing reconstruction algorithms for multispectral imaging.

### 1.3 Hyperspectral Denoising

A problem that often occur in image acquisition process is the denoising problem. An image is said to be noisy if it contains undesired or missing information. This unwanted information can be in the form of a random signal that causes a change in actual intensity value at some or all pixels in the image. Image denoising is a classical problem as images often get corrupted by noise at any level of processing from image acquisition to image archiving in memory. Various kinds of noise may be simultaneously present in an image such as Gaussian noise, random-valued impulse noise, salt and pepper noise, shot noise, line strips, etc. Figure 1.6 shows an example of denoising problem. Here the original image is corrupted by three kinds of noise, and the captured image is the noisy image. The denoising problem is to recover the original image given the observed noisy image. When the image is corrupted by several kinds of noise, then the problem is called mixed-noise reduction problem.

![Mixed noise reduction problem](image)

The most common type of noise is Gaussian noise that corrupts each pixel in the image by some amount. Random valued impulse noise corrupts few pixels in the image but corrupts them heavily by some random amount. Salt-and-pepper noise is an extreme case of random-valued impulse noise in which corrupted pixels values become either zero or one. Shot noise and line strips mostly occur in satellite images. In the case of shot noise, a particular pixel gets corrupted in all the bands. The line-strip problem is the presence of partial or full horizontal or vertical lines in the image depending on the type scanners.

Images are corrupted by noise due to several reasons including fluctuations in power supply, dark current, non-uniformity of detector response, etc. A real hy-
A perspectral image may get corrupted by several kinds of noise including Gaussian noise, random-valued impulse noise, salt-and-pepper noise, horizontal and vertical deadlines, etc. Therefore, hyperspectral denoising is a mixed noise reduction problem consisting of a mixture of Gaussian noise and sparse noise. The term sparse noise [20] refers to the noise that corrupts only a few pixels in the image but corrupts them heavily. The sparse noise includes random-valued impulse noise, salt-and-pepper noise, horizontal and vertical dead-lines.

The noise that occurs due to conditions like poor lighting, dark current or sensor noise is found to obey Poisson distribution and is approximately modeled as additive Gaussian noise. This noise enters into the system while capturing an image. Horizontal line strips often occur in images captured by whisk-broom kind of sensors that have rotating mirrors perpendicular to the flight direction. Vertical line strips mostly occur in images taken by the push-broom type of sensors which capture scene along the flight direction. Shot noise occurs due to some defective pixels. Random fluctuations in the power supply of satellite’s sensor often corrupt these images by random-valued impulse noise. Images also become noisy due to dark current and non-uniformity of detector response.

Figure 1.7 shows a portion of band 134 and band 132 of WDC image as an example of a noisy and a clean image. It can be observed that band 134 have some undesirable information in the form of some horizontal lines whereas band 132 is comparatively very sharp. The aim of hyperspectral denoising is to reduce the unwanted information from corrupted bands.

![Figure 1.7: Real noisy hyperspectral image](image_url)

If there is noise in a hyperspectral image, then the best option is to recapture it, but often this is not possible because of several reasons. It might be not possible to reorient the satellite to that geographical location also the cycle time of satellite may be very long. Instantly, it might not be possible to check image for the presence of noise because there is a time gap between the image being captured and received on the Earth. Also, sometimes denoising become essential if some non-repeatable natural
Hyperspectral denoising is an important pre-processing step in various applications of hyperspectral images such as terrain classification and target detection. Hyperspectral denoising is a classical well studied problem \([21–26]\). There are studies such as \([27–29]\) which consider mixed noise reduction from gray-scale images. These studies analyze mixture of only Gaussian and salt-and-pepper noise whereas we address a realistic scenario by taking into account more general noise and attempt to solve this problem for hyperspectral images. A recent low-rank matrix recovery (LRMR) based denoising approach \([20]\) can reduce mixed noise from hyperspectral images. The low-rank based model is a global model which, in the context of hyperspectral images, exploits spectral correlation whereas total variation is a local model that utilizes spatial correlation within a band.

1.4 Hyperspectral Unmixing

If an observed signal consists of several source signals then the problem of identifying each component signal from that mixture is called source separation problem. This problem occurs in many application areas such as speech processing, medical imaging, remote sensing, etc. In the context of hyperspectral images, the source separation problem is called the unmixing problem. Hyperspectral unmixing is a classical, important, and challenging problem in remote sensing. It is a problem of identifying endmembers and their fractional abundances present at every pixel in a hyperspectral image. The term endmember refers to various materials that may be directly or indirectly present in a hyperspectral image. The term direct-presence indicates the existence of pure pixels, and indirect presence refers to mixed pixels. A pixel in a satellite image corresponds to an extensive spatial area on earth as demonstrated in Fig. 1.8. This spatial region constituting that pixel may be covered by a single object or multiple objects. If the area covered by a pixel forms a single object then such a pixel is called pure pixel; otherwise, it is called mixed pixel. The term fractional abundance indicates the percentage of a particular endmember present at a pixel. Thus, abundance map shows the distribution of a particular endmember over a region. The pure pixels have the fractional abundance of one whereas mixed pixels have fractional abundance.
between zero and one. The unmixing problem can be categorized as linear or non-linear. Figure 1.8 shows the linear unmixing problem for a pixel of a hyperspectral image. The linear unmixing problem considers each pixel as a linear combination of several available endmembers. The non-linear unmixing problem also accounts for the interaction between various endmembers constituting that pixel.

Hyperspectral unmixing has applications in various domains such as geology, agriculture [30], environmental studies, biology [31], etc. The abundance maps are often used as feature vectors [32] in several image processing and pattern recognition related applications of hyperspectral images. Hyperspectral unmixing is also utilized in denoising [33], data fusion [34], and super-resolution [35] related applications.

If a hyperspectral image is of very high resolution, then its constituent endmembers shall be considered at micro level such as chemical composition of the pixel. These images require the unmixing problem to be handled at the micro level. However in this work, we are interested in the macro level decomposition of a pixel into its constituent components. An overview of hyperspectral unmixing algorithms has been discussed in [36].

Often hyperspectral images are corrupted by some kinds of noise as discussed in the previous section; therefore, it is desirable to do unmixing of hyperspectral images even when they are corrupted by one or several of these kinds of noise. This problem of unmixing in the presence of mixed noise can be approached by first applying a denoising algorithm followed by the unmixing algorithm. This work directly recovers the abundance map in the presence of mixed noise. There are studies such as [26, 33] that also perform unmixing in the presence of noise. This work is different from these existing methods in both the noise model and the solution approach.

This work is based on linear mixing model for unmixing as shown in Fig. 1.9, however, there are various nonlinear models for the hyperspectral unmixing whose survey can be found in [37]. The work focuses on the sparse unmixing problem in which each pixel can be represented as linear combination of few endmembers out of hundreds of available endmembers as shown in the Fig. 1.9. Columns of the abundance matrix in this Figure shows sparse coefficients corresponding to each pixel.

![Figure 1.9: Sparse linear unmixing model](image-url)

There are algorithms such as pixel purity index (PPI) [38] and N-FINDER [39] which require the presence of pure pixels in the image. However this pure pixel assumption may not be true always, and therefore, this work proposes to do unmixing in the absence of pure pixels. Hyperspectral unmixing approaches can be categorized as the one that utilizes existing spectral libraries and others that try to estimate endmem-
ber spectral signatures using non-negative matrix factorization based techniques such as [40]. This work is based on utilizing existing spectral libraries available for many materials in different categories of endmembers such as artificial, minerals, soils, etc.

This work intends to utilize the mixed noise model proposed in [41] that was later employed for denoising in [20]. This model allows us to formulate the linear hyperspectral unmixing problem that explicitly account for both Gaussian and sparse noise. The total number of endmembers available from different spectral libraries (e.g. the USGS library) are enormous, but only a few of these endmembers are present in a given hyperspectral image. At every pixel, a subset of the endmembers (present in the whole image) is present. This observation can be modeled as joint-sparse [42] regularization on abundance maps. Natural images often exhibit high spatial correlation implying that pixels having the same spectral signature may be present in the neighborhood. This observation can be modeled as total-variation [43] regularization on abundance maps. Thus, this work proposes a hyperspectral unmixing algorithm that utilizes generic noise model and explores both joint sparsity and spatial smoothness of abundance maps. The resulting optimization problem is solved using the split-Bregman [44] based technique. Our work improves over the state of the art sparse regression based unmixing techniques sparse regression (SR) [45] and its variants total variation spatial regularization (SRTV) [46] and collaborative sparse regression (CLSR) [47].

1.5 Hyperspectral Classification

Data classification is a well studied problem in machine learning. It primarily involve grouping the data items into classes based on the similarity among data items. Data classification task can be broadly categorized as supervised classification or unsupervised classification. When there exists training data to learn a classifier then it is called supervised classification whereas when no training data is available then grouping of data is done in an unsupervised manner popularly known as clustering. There are many approaches to perform classification such as decision trees, support vector machine (SVM), neural networks (NN), k-nearest neighbor (KNN), etc.

KNN is one of the simplest classifier. It takes a test sample and identifies K-nearest training samples. The class label can be decided using the majority voting technique. Figure 1.10 describe the working of KNN classifier on two-class classification problem. It can be observed from Fig. 1.10 that KNN classifier is dependent on the choice of k.

![Figure 1.10: K-nearest neighbor classifier](image)

When k=3 then test sample gets assigned to class 1 whereas when k=5 then test sample
gets assigned to class 2.

The nearest subspace classifier (NSC) can be thought of as an extension of KNN classifier. It assumes that all the data samples belonging to a particular class lies in a subspace. Therefore, each test sample is assigned a class label based on the distance of the test sample from different training subspaces. Figure 1.11 shows an example of how nearest subspace classifier works. In this example, the distance of given test sample is calculated from both the subspaces and since it is near subspace 1 therefore, it gets assigned to class 1 (red cross).

![Nearest Subspace Classifier](image)

**Figure 1.11: Nearest subspace classifier**

The sparse regression based classifier does not make any such assumption and it tries to find a sparse representation of each test sample using all the training samples as described in the Fig. 1.12. All the training samples from different classes are used as a dictionary to find the sparse representation of each test sample. The sparse coefficients of each test sample corresponding to the training data of each class are then used to find the approximation of the test sample. The label of a class whose training data gives best approximation of a test sample, gets assigned to that test sample.

![Sparse Regression Based Classifier](image)

**Figure 1.12: Sparse regression based classifier**

The classification is performed either on the raw data or sometimes features are extracted from the data which are then classified. The features are often extracted with the intention of reducing the dimensionality, reducing the effect of noise, increase the class separability, increasing the speed of classification algorithm, etc.

The hyperspectral image classification is an important application that finds use in many areas such as land-cover change detection, urban planning, environmental monitoring, etc.. It is different from ordinary image classification problems where several images are available and each image belong to a single class. In hyperspectral
image classification, a large image of the study area is available in which each pixel is required to be assigned a particular class label. Each pixel of a satellite image covers a large ground area that make it challenging to manually collect lot of training data therefore hyperspectral image classification become challenging due to limited training data.

If the images are of very high spatial resolution then pixels of different classes can have very similar spectral signature that makes it difficult to classify at pixel level. Often super-pixel based classification or object based classification techniques are found suitable in that situation to reduce the dimensionality of the dataset. If the images are of very low spatial resolution then a pixel may consist of several classes then unmixing techniques are often applied to find the fraction of different materials present in that pixel and then label of the class with highest abundance may be assigned to that pixel.

Feature extraction is often required to reduce the high dimensionality of hyperspectral datasets. Various feature extraction techniques has been proposed in literature for hyperspectral feature extraction including principle component analysis (PCA), variations of wavelet transforms, dictionary learning based features, etc.. Different kinds of band ratios such as normalized difference vegetation index, normalized difference water index, Soil Adjusted Vegetation Index, normalized difference built-up index are often used to extract vegetation, water, soil, and urban areas respectively.

1.6 Research Contributions

This thesis focuses on four inter-related problems. The first one is on acquisition of multi-spectral images. From a signal processing driven perspective, we propose filter design and reconstruction techniques for single sensor multi-spectral cameras. The second problem is denoising of hyper-spectral images; this is a low-level image processing operation which usually follows acquisition. The third problem is that of unmixing. This is a unique step in hyper-spectral imaging which succeeds preprocessing (denoising) and precedes image analysis. The fourth and final problem is that of hyper-spectral classification- which is usually an automated image analysis problem.

The research contributions are summarized as follows:

- **Multispectral Demosaicing**: A generic filter array design has been proposed to capture multi-spectral images using hypothetical single-sensor multi-spectral cameras. The design idea is based on the uniform sampling of intensity values from each band irrespective of spectral properties of any particular band. A reconstruction technique has also been proposed to interpolate unknown intensity values of other bands at each pixel. The proposed method was evaluated on both color and multispectral image datasets. Quantitative evaluation of the proposed technique was done using peak signal to noise ratio.

- **Hyperspectral Denoising**: The denoising problem has been formulated as a mixed noise reduction problem. A general noise model has been considered
which accounts for not only Gaussian noise but also sparse noise. The inher-
ent structure of hyperspectral images has been exploited by utilizing two ap-
proaches. The first method simultaneously exploits sparsity along spatial di-
mension using 2D DCT and spectral sparsity using 1D DCT whereas the second
procedure considers 2D-total variation along the spatial dimension and 1D-total
variation along the spectral dimension. In both the cases, the denoising problem
has been formulated as an optimization problem whose solution has been de-
\[ \text{Hyperspectral Unmixing} \quad \text{The hyperspectral unmixing problem is considered}
\]
\[ \text{in a general scenario that includes the presence of mixed noise. The unmixing}
\]
\[ \text{model explicitly takes into account both Gaussian noise and sparse noise. The}
\]
\[ \text{unmixing problem has been formulated to exploit joint-sparsity of abundance}
\]
\[ \text{maps. A total-variation based regularization has also been utilized for mod-
}\]
\[ \text{eling smoothness of abundance maps. The split-Bregman technique has been}
\]
\[ \text{employed to derive an algorithm for solving resulting optimization problem.}
\]
\[ \text{Detailed experimental results on both synthetic and real hyperspectral images}
\]
\[ \text{demonstrate the advantages of proposed technique.}
\]
\[ \text{Hyperspectral Classification} \quad \text{The hyperspectral classification problem is con-
}\]
\[ \text{sidered from the dictionary learning perspective. A general deep dictionary}
\]
\[ \text{learning framework has been proposed that learn the dictionary in a greedy fash-
}\]
\[ \text{ion by avoiding the need for back-propagation. We compare our approach to the}
\]
\[ \text{deep belief network (DBN) and stacked autoencoder (SAE) based techniques on}
\]
\[ \text{standard hyperspectral classification datasets.}
\]

The research outcomes have been disseminated through publications in journals
and conferences listed at page 91.

\[ \text{1.7 \ \textbf{Dissertation Organization}} \]

Chapter 2 gives a description of some important basic concepts that are building
blocks of this thesis. It includes a brief description of what is compressed sensing
and its variants such as blind compressed sensing and Kronecker compressed sens-
ing. Concepts related to dictionary learning and joint-sparsity are also discussed along
with low-rank minimization and total variation minimization.

Chapter 3 discusses the multispectral demosaicing problem which is an extension
of the color image demosaicing problem. This chapter also describes how demosaic-
ing problem can be formulated as parameter estimation problem by simultaneously
utilizing nearby band information. Since there is no standard filter array to capture multispectral images, therefore, a description of proposed uniform multispectral filter array is also contained in this chapter.

Chapter 4 describes hyperspectral denoising problem formulated as a sparse recovery problem. First, a mixed noise model is described followed by brief literature review. Proposed noise reduction algorithms based on 3D-discrete cosine transform and 3D-spatio-spectral total variation are described. This chapter also presents comparative results with some standard denoising algorithms.

Chapter 5 is based on source separation problem in the context of hyperspectral images. First, the unmixing problem is described that how it can be modeled as a linear inverse problem. A description of terminology specific to the unmixing problem is also described. A solution based on joint-sparsity and total variation is the presented followed by detailed synthetic and real dataset experiments.

Chapter 6 introduces deep dictionary learning for hyperspectral image classification. First, the problem is described followed by some literature review. The greedy dictionary learning approach is then detailed followed by experimental results on standard hyperspectral image classification datasets. Finally, chapter 7 concludes the thesis with some limitations and future work.