RESOLUTION ENHANCEMENT OF MULTI-LOOK IMAGERY

by
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ABSTRACT

This dissertation studies the feasibility of enhancing the spatial resolution of multi-look remotely-sensed imagery using an iterative resolution enhancement algorithm known as Projection Onto Convex Sets (POCS). A multi-angle satellite image modeling tool is implemented, and simulated multi-look imagery is formed to test the resolution enhancement algorithm. Experiments are done to determine the optimal configuration and number of multi-angle low-resolution images needed for a quantitative improvement in the spatial resolution of the high-resolution estimate. The important topic of aliasing is examined in the context of the POCS resolution enhancement algorithm performance. In addition, the extension of the method to multispectral sensor images is discussed and an example is shown using multispectral confocal fluorescence imaging microscope data. Finally, the remote sensing issues of atmospheric path radiance and directional reflectance variations are explored to determine their effect on the resolution enhancement performance.

CHAPTER 1

INTRODUCTION

1.1 Motivation

Remote sensing imagery plays a key role in our understanding of the composition of the earth's surface both spatially on a global scale and temporally with each season or from year to year. Since the launch of the first Landsat satellite in the early 1970s, new sensor approaches are continually being developed to improve upon our ability to quantitatively assess the earth's resources. A sensor design that has been exploited recently is one based upon multiple look angles to improve upon the knowledge of directional radiance leaving the earth's surface or to assist in understanding the atmospheric effect on surface-leaving radiance. Increased resolution of satellite sensors has been a major goal over the years; imaging technology has improved dramatically over the last three decades. New commercial satellites such as IKONOS [1, 2] and Quickbird [3, 4] have ground resolution finer than one meter. Although such fine resolution is not needed for some applications, such as global mapping of ocean currents or drought conditions, many customers of remote sensing imagery desire the highest spatial-resolution images that are available. Urban planning, military planning, intelligence, and disaster monitoring/evaluation are several tasks in which very high spatial resolution is needed. However, many

objects of interest for these tasks, such as cars, roads, and buildings, are small compared to the ground resolution of most satellite-based sensors. In places that are difficult or impossible to reach on foot, the ability to zoom in on an area of interest using a space-based camera is invaluable. Even for tasks requiring global coverage, higher spatial resolution is desired. If a computer existed that was powerful enough to store imagery of the entire earth at a one-inch ground resolution, there would be someone who could use that data (to measure urban boundaries, or to monitor the total number of fires burning globally, detect the appearance of new forest fires, etc.).

There are several issues to consider pertaining to spatial resolution. Size and weight limitations of the satellite leads to a problem of attaining higher spatial resolutions. Telescopes, for example, become more powerful as the lens or light-focusing mirror gets larger; the Hubble telescope had to fit within the Space Shuttle cargo bay, fundamentally limiting its resolution. For multispectral sensors, there is a tradeoff between spectral and spatial resolution when designing a system. Multispectral systems often require multiple detector arrays, one for each spectral band, which are expensive; by lowering the spatial resolution of each detector, more bands may be put on the sensor for the same cost. Another difficulty is the storage and processing of high-resolution imagery. While desiring higher and higher resolution imagery, more and more storage and processing time are needed to handle the increased file sizes.

An alternative way to increase image resolution is to design the sensor system to acquire images at a lower resolution and use the sensor system's pointing capabilities to allow collection of multiple low-resolution images within a short time span as the sensor travels over a target area. Then, image processing methods to fuse the multiple low-resolution images into a single high resolution image may be used [5–7]. These methods are called *resolution enhancement* algorithms, or *super-resolution image reconstruction*. Resolution enhancement algorithms rely on the fact that sub-pixel surface features moving around in the sensor's field of view (FOV) can allow these features to be resolved on a finer sampling grid. Applying these resolution enhancement algorithms to satellite imagery acquired by rapid pointing maneuvers adds considerable complexity to the problem. The images have geometric distortions due to different satellite view angles, have a variable ground sample distance (GSD) due to the changing optical path length from the sensor to the ground at different view angles, and are affected by atmospheric conditions and directional reflectance effects from surface materials. These other effects should be removed if feasible so that changes in the sensor output are only due to the surface feature and not atmospheric and bidirectional reflectance distribution function (BRDF) effects.

Several satellite-based imaging systems have the ability to quickly acquire images at different view angles. These include the Multispectral Thermal Imager (MTI) [8, 9], IKONOS [1, 2], Quickbird [3, 4], the Multi-angle Imaging Spectro-Radiometer (MISR) [10], the Along Track Scanning Radiometers (ATSR-1, ATSR-2, AATSR)

[11], and the Compact High Resolution Imaging Spectrometer (CHRIS) [12, 13]. The “agility” of a pointable spacecraft varies from platform to platform, limiting the number of images that may be imaged in a single pass over a ground target. For instance, the MTI instrument was designed to acquire two images of a tasked ground target, while the CHRIS instrument on the Project For On-Board Autonomy (PROBA) mission is capable of collecting five images on a single overpass [13]. The MISR instrument collects nine images, but does so by using nine cameras at fixed angles rather than pointing a single camera. It is difficult to estimate the maximum number of images that a particular sensor is capable of collecting during an overpass; many factors are involved, including the slew rate of the platform under constraints of maximal torque, the amount of on-board memory, data transfer rates, attitude control procedures, and other overhead processing that is highly dependent on the design of the image acquisition control software.

This dissertation focuses primarily on studying the feasibility of enhancement of data from the MTI, which was designed to acquire two images for each scene of interest. However, the experiments use simulated off-nadir imagery in order to have control over the image registration and view angle parameters, as well as to provide sufficient data for analysis. A detailed description of the MTI sensor follows in Sect. 1.2. An overview of steps required to correctly apply resolution enhancement algorithms to multi-look remotely-sensed images is given in Section 1.3. Subsequent chapters will address the details of each processing step required.

1.2 Multispectral Thermal Imager: MTI

The Multispectral Thermal Imager (MTI) is a U.S. Department of Energy research satellite with fifteen spectral bands, from the visible to the thermal infrared [8, 9]. The MTI is a *pushbroom sensor*; i.e., it has linear detector arrays oriented in the cross-track direction. The cross-track direction is perpendicular to the direction of motion of the satellite. Each spectral band has its own linear detector array that is filtered to collect light in a desired spectral region. As the satellite travels, a two-dimensional image is formed for each band, with a GSD in the cross-track direction determined by the detector element size, the elevation of the satellite above the ground, and the satellite look angle (discussed below); the GSD in the along-track direction also depends on the detector integration time, and the speed and pitch of the satellite motion. An illustration of the pushbroom sensor design is shown in Fig. 1.1. For near-nadir images, the ground sample distance is approximately 5 meters for the visible and the near-infrared bands (bands A through D), and 20 meters for the midwave and the thermal bands (bands E through O).

Figure 1.2 shows the layout of the MTI focal plane. The focal plane contains three sensor chip assemblies (SCAs), each consisting of linear detector arrays for each band. The purpose of multiple SCAs is to increase the crosstrack field of view (nominally 12 km). The line detectors for the visible and near infrared (VNIR) bands are located near the center of the focal plane where the optical quality is highest. Each line detector has a delayed start time for readout, so that the 48

Figure 1.1: Pushbroom sensor

images (3 SCAs, 16 line detectors each) are collected sequentially in time, about 4.5 seconds for all of the bands to acquire a 12 km by 12 km image [14]. The visible/NIR bands (A-D) are arranged in a staggered pattern to reduce crosstalk and increase the signal-to-noise ratio. Also, there are redundant line detectors for bands E to O. Both line detectors for band H are read out, resulting in an H1 and an H2 band. Bands E-G and I-O also have two line detectors apiece, but active and inactive detectors are selected, resulting in only the active detectors being turned on for a given image acquisition. In practice, one complete line detector is activated to acquire each band, rather than picking and choosing detectors as shown here. Nonetheless, the satellite does have that capability.

Figure 1.2: Layout of the MTI focal plane

To increase the system's image acquisition flexibility, the MTI satellite has pointing capabilities, meaning that an image can be taken off to a side, forward, or behind at a given *look angle*. Pointing allows the MTI to acquire a *two-look* image. First, an image is taken with the camera pointing (almost) straight down at a target on the Earth's surface. This image is called the *nadir* image. The target is usually located some distance away from the satellite's orbital track in the cross-track direction, so the nadir image look angle is not exactly zero; rather, it is as close to a nadir angle as is possible given the current orbital position of the satellite, but at least within 20 degrees of nadir. After the satellite has continued in its orbit for a short time, on the order of a few minutes, it then points back at the first target location and acquires a second, *off-nadir* image. The off-nadir image is taken with a look angle of 50 to 60 degrees, typically. The number of images that may be taken in a single overpass is limited by the time required to reorient the satellite. In theory, more images could be taken, but this has not been done during MTI collects. The cross-track pointing has a range of ± 20 degrees, and the along-track pointing has a range of ± 60 degrees. With an orbit height of 575 km and a satellite speed of 7 km/sec, the MTI has a little under 5 minutes in which it must point at and acquire its target scene. An illustration of two-look image acquisition is shown in Fig. 1.3.

The spatial resolution of the off-nadir image is poorer than that of the nadir image because the extent of the projection of a detector onto the ground, or GSD, is a factor of $\cos^2 \theta$ larger, as shown in Fig. 1.4. The off-nadir GSD in the along-track

Figure 1.3: Two-look imaging, showing nadir and off-nadir viewing

direction is given by

$$\text{GSD}_\theta = \frac{\beta h}{\cos^2 \theta} = \frac{\text{GSD}_n}{\cos^2 \theta} \quad (1.1)$$

where GSD_n is the nadir ground sample distance, θ is the angle from nadir, β is the angular instantaneous field of view (IFOV), and h is the distance from the sensor to the ground [15, 16]. This simplified diagram does not account for satellite motion or the detector integration time, which increase the nadir and the off-nadir along-track GSD. The cross-track GSD is similar to the along-track GSD, but scales by $\cos \theta$ rather than $\cos^2 \theta$, resulting in an oblong projection of each pixel onto the ground.

Figure 1.4: Off-nadir vs. nadir ground sample distance.

1.3 Overview of Multi-look Resolution Enhancement

The goal of this dissertation is to create a single high-resolution image from multiple low-resolution images taken at different look angles. Several processing steps are used to combine multi-angle images into a single high resolution image, as shown in Fig. 1.5. Each image, or “frame,” may be optionally pre-processed to compensate for atmospheric and BRDF effects. Then, the frames are aligned with each other, or registered. The co-registered, corrected frames are then input to a resolution enhancement algorithm that synthesizes a high resolution image.

Figure 1.5: Flow diagram of resolution enhancement processing for multi-angle remotely-sensed imagery.

An overview of each step required for multi-angle resolution enhancement is given in subsequent chapters, using Fig. 1.5 as a guide. Since resolution enhancement is a well-developed field of research, the primary goal for this dissertation was to determine which type of enhancement algorithm is best suited for the unique problems inherent to multi-look remotely-sensed imagery, and to analyze the effects of those

problems on the performance of a chosen enhancement algorithm. A review of resolution enhancement algorithms is given in Ch. 2, with emphasis on those algorithms most useful to combine multi-angle remote sensing imagery. The Projection Onto Convex Sets (POCS) resolution enhancement algorithm is applied for the first time to multi-angle satellite imagery in this dissertation. Chapter 3 describes the modeling of multi-angle imagery, for use in testing the applicability of resolution enhancement algorithms to a set of remotely-sensed images acquired at different angles. Results of applying the resolution enhancement algorithm to simulated multi-angle imagery are shown in Ch. 4. We demonstrate that multi-look resolution enhancement is feasible by combining as few as two images. A major contribution of this work is a study of the effect of aliasing on resolution enhancement. Aliasing is shown to be an important issue for resolution enhancement in the context of remote sensing; for multispectral sensors, the aliasing present in the different spectral band images can vary. Better resolution enhancement occurs if the set of low-resolution input frames have more aliasing, while it is hard to improve upon non-aliased imagery. Prior research assumed that the low-resolution frames were aliased, but did not quantify the amount of aliasing or model its effect on POCS performance. The preprocessing steps of atmospheric correction and BRDF correction allow further refinements to the resolution enhancement processing; their effects are discussed in Ch. 5. It is shown that atmospheric correction is important for images at off-nadir angles of $\theta > 40^\circ$, and that BRDF effects are detrimental for $\theta > 20^\circ$. These results

demonstrate that multi-angle resolution enhancement is possible, but that modifications to the image acquisition process to minimize atmospheric and BRDF effects may be necessary for good results with real rather than simulated imagery.

CHAPTER 2

RESOLUTION ENHANCEMENT ALGORITHMS

2.1 Resolution: Terms and Definitions

Before reviewing the field of resolution enhancement, some definitions are necessary to clarify terminology used in remote sensing and in digital image processing. *Remote sensing* is the process of measuring an *object* at a distance (or observing a *scene*) using an *imaging system* or *sensor*. A *propagation medium* separates the sensor from the object to be measured. The output of the system is called an *image*. Most remote sensing imaging systems today are digital, meaning that light is collected on *detector arrays* rather than film. Photons reaching the detector array are recorded at discrete positions, leading to the concept of *digital image spatial resolution*. A two-dimensional CCD array, for instance, contains a finite number of detectors. The detector measurements are stored in a computer as a digital image, with each *pixel* corresponding to the output of one detector. The spatial resolution of a digital image may be given in numbers of pixels in each of two dimensions, or, equivalently, in the number of detectors. However, in remote sensing, spatial resolution must be more precisely defined. The distance from the detectors to the ground, as well as the number of detectors, determines the smallest observable feature in a scene. The size of each detector determines the size of the spatial area in the scene

from which photons are collected for a single pixel. This occurs because an imaging system focuses light from a large area onto a small detector with a *lens* or a *mirror*. In the image space, a detector has a spatial dimension that maps to an area in the object space through the imaging system *magnification factor*. Projecting the optical path from a detector back through an imaging system, through a medium, and onto the object being measured (on the ground) gives the *ground sample distance* (GSD) for each detector. For a pushbroom system like the MTI, the integration time determines the along-track GSD, as discussed earlier in Sect. 1.2. Spatial resolution may be given in either the coordinates of object space or of image space; for remote sensing, the GSD is the measurement of interest for determining spatial resolution. *Resolution*, in this dissertation, refers to the GSD or spatial resolution in object space. As an aside, the digital numbers (DN's) corresponding to the values stored for each pixel also have a *DN resolution*, which describes the quantization of the DN values. Clearly, resolution is an overloaded term and must be used carefully.

2.2 Goal of Resolution Enhancement

Given a set of low resolution images, the goal of resolution enhancement is to form a single image with higher resolution, so that the effective GSD is improved. Improving the GSD by combining data from several images will allow finer detail to be seen in the image by a human analyst, and will allow better localization of the edges of the features in an image. Forming an image at a higher resolution than

that of any of the low resolution images is possible if enough unique information is available; luckily, this is usually the case. Low resolution digital images are typically aliased (subsampled). If they are shifted with respect to one another with subpixel precision, more information is available than with a single image. Conceptually, this is shown in Fig. 2.1.

Figure 2.1: Subpixel shifts provide unique information.

The interleaving of low resolution images is useful to visualize the idea behind resolution enhancement, but is overly simplistic. Quantitatively, an observation model is needed to relate the desired high resolution (HR) image to the observed low resolution (LR) images, or frames. This model is shown in Fig. 2.2.

The LR frames are warped, blurred, and downsampled observations of the HR image, and may have additive noise. Warping can involve translations, rotations,

Figure 2.2: Observation model relating low resolution (LR) images to a high resolution (HR) image.

skew, or projective distortion from one LR frame to another. Blur may be due to many reasons, including diffraction-limited optics, motion of the imaging system, motion of the viewed objects, or atmospheric turbulence. Sampling by a CCD array discretizes the locations of incoming photons. Noise from the imaging system’s detectors (shot noise) and other electronics also degrades the LR images.

To briefly digress, one could ask why an optical system’s detectors are not simply made smaller to acquire images with well-localized edges, rather than use algorithms to improve the resolution. Unfortunately, there is a physical limit on the detector size: the signal-to-noise ratio (SNR) becomes too small if the detector is made too small. The current lower limit for detector area is close to $40\mu m^2$ using a $0.35\mu m$ CMOS process [7]. Consequently, for some imaging systems, the option to reduce the detector size does not exist. And, for most systems currently in orbit, the detectors cannot be replaced.

Using the observation model above, the LR images may be input to an algorithm that tries to remove the degradations of the imaging process while using the unique

information contained in each LR frame, resulting in an estimated HR image. The resulting HR estimate is discrete (sampled), but is not aliased, and is sampled to a finer grid than any of the sampling grids of the LR frames.

With the goal of resolution enhancement now explained, the theory of resolution enhancement may be discussed. Resolution enhancement of images combines several concepts of digital image processing in a single algorithm. These concepts are:

- Image restoration
- Image resampling and interpolation
- Image fusion
- Super-resolution

They will be explained in the following sections.

2.3 Image Restoration

Image restoration attempts to remove degradations in an image, such as blur and noise. A model for the degradations is assumed or estimated, then the inverse of the model is used to estimate the undegraded object. A comprehensive review of digital image restoration is given in Ref. [17], with relevant points summarized here. Early motivation for digital image restoration came from the desire to correct the degradations seen in imagery acquired by the first planetary science missions such as the Lunar Orbiter and Mariner [17]. In classic image restoration algorithms,

the output grid has the same number of pixels as the input grid. To do resolution enhancement, the output grid must have a greater number of pixels than the input grid; thus, image restoration is only part of the process.

A linear model for the degradations is typically used in restoration algorithms,

$$g(i, j) = \sum_{k=1}^M \sum_{l=1}^N h(i, j; k, l) f(k, l) + n(i, j) \quad (2.1)$$

where g is the $M \times N$ degraded image, f is the $M \times N$ object to be restored, h is the two-dimensional point spread function (PSF) of the imaging system, and n is additive noise. If the blur does not vary spatially, this imaging system model may be simplified to a linear shift-invariant model,

$$g(i, j) = \sum_{k=1}^M \sum_{l=1}^N h(i - k, j - l) f(k, l) + n(i, j) \quad (2.2)$$

$$= h(i, j) ** f(i, j) + n(i, j), \quad (2.3)$$

where $**$ represents a two-dimensional convolution operator [18]. The imaging model for an $N \times N$ degraded image may be also written as

$$\mathbf{g} = \mathbf{H} \mathbf{f} + \mathbf{n}, \quad (2.4)$$

where the image $\mathbf{g}$, object $\mathbf{f}$, and noise $\mathbf{n}$ are $1 \times N^2$ vectors formed by scanning the 2D images row by row (or column by column), and $\mathbf{H}$ is an $N^2 \times N^2$ blur matrix. To solve for the object $\mathbf{f}$, the inverse of the blur, $\mathbf{H}^{-1}$, must be found and applied to the degraded image $\mathbf{g}$.

2.4 Image Resampling and Interpolation

Resampling algorithms re-orient images and may increase or decrease the size of the sampling grid. Image resampling is often needed in remote sensing. It is used to put the samples from different bands of a multispectral sensor on a common grid, to align images so that the top of the image points north (called georectification), and allow fusion of images from multiple sensors. Images from different sensors must be resampled to facilitate their use with one another because they acquire their imagery in different orientations and with differing ground sample distances (GSDs). Resampling must be done with care to preserve the image quality. Multiple resampling of data is considered non-ideal because it degrades the radiometric quality of the data. The resampling of MTI imagery is discussed in [19].

Resampling an image from one regular grid to another, more finely-spaced, regular grid is called interpolation. Digital image processing techniques to interpolate an image to a larger sampling grid have been used for decades. These methods include nearest neighbor, bilinear interpolation, cubic convolution, and cubic b-spline. They may not be appropriate for interpolation of remotely sensed images because nonuniform sampling of pixels, pixel overlap on the ground, and changing pixel size with image acquisition geometry all present problems for these traditional methods [20]. However, they are computationally fast compared with more sophisticated algorithms, so are widely used.

There are some interpolation methods that have been used with nonuniform sample grids. A resampling technique called “optimal” interpolation has been applied to irregularly-spaced data points from the Advanced Very High Resolution Radiometer (AVHRR) sensor [20]. AVHRR is a line scanner (or whiskbroom system), which forms an image using a single detector and a mirror that spins to “scan” each line in the cross-track direction as the satellite moves in the along-track direction [21]. The detector output is sampled to create each pixel. Each cross-track sweep covers a distance on the ground called the field of view (FOV). At the far edges of each sweep, the pixel size is larger since it is viewing off at an angle. Using this off-nadir data is difficult since successive lines overlap and the pixel projections onto the ground change size with varying angle. This “bowtie” effect is also discussed in [21]. To meet the challenge of using AVHRR data at increasingly off-nadir angles, Moreno and Melia [20] applied an “optimal” interpolation method that had been previously applied to microwave image data [22]. The theory was originally developed by Backus and Gilbert to find localized averages of the earth’s structure at different depths [23]. The method calculates a resampled pixel value using a weighted linear combination of neighboring pixel values, where the weights are determined by each pixel’s point spread function. Similar research on resampling of irregularly-spaced data goes back many decades. Yen wrote a paper in 1956 on nonuniform sampling [24]; he refers to even earlier observations by Cauchy in 1841 on the topic. Chen and Allebach discussed errors in reconstructing signals from

irregular samples in [25]. An area of research called signal and image reconstruction has resulted in direct and iterative methods to interpolate irregularly-spaced data points, including the estimation of missing data points in an image. Comparisons of iterative and direct reconstruction methods are given in [26–28] and reviewed in [29].

2.5 Image Fusion

Multiple images are combined into one image during image fusion, but increased resolution is not always the goal. Often, the goal in image fusion is to create an output image that is more useful for further analysis than any of the individual input images. There are many types of image fusion, including multi-sensor fusion, multi-temporal fusion, multi-band fusion, and multi-resolution fusion.

In multi-resolution image fusion, for instance, high-resolution panchromatic bands are fused onto lower-resolution IR bands, which aids image analysis by getting better edge localization in the IR bands. Many ad-hoc algorithms of its type have been devised; the images combined are not necessarily of the same physical units (such as radiance or reflectance), resulting in radiometric mixing. However, it is important for most remote sensing algorithms to preserve the radiometric fidelity of the data collected by a sensor – the images are carefully calibrated in order to determine the physical quantities, such as temperature, of materials in a scene. These direct measurements are then used by remote sensing researchers to derive

secondary measurements, such as estimates of the warming or cooling of the atmosphere. Therefore, multi-resolution image fusion can enhance the visual analysis of low-resolution data, but in general should not be used for deriving secondary data products.

Resolution enhancement may be considered a subset of image fusion, because multiple images are combined to form an image that may have increased interpretability, in this case because the pixel size is made smaller. By contrast, compositing is an image fusion method used in remote sensing that does not enhance resolution [30]. Remote sensors with a wide field of view and a polar orbit, such as MODIS and AVHRR, allow global coverage of surface features over time. Compositing algorithms are used in order to make global maps using data from these sensors. After registration of the separate images, co-located pixels/data points may be combined or a single data point may be selected for that pixel location in the composite image. However, the output pixels are the same size as the input pixels; no resolution enhancement occurs. As mentioned in Ref. [30], an algorithm has been implemented that removes the BRDF effects prior to compositing to form combined nadir estimates of the surface reflectance, the NDVI, and the surface temperature [31].

2.6 Super-resolution

Super-resolution is the extrapolation of the frequency content in an image, permitting the reconstruction of a digital image onto a grid with smaller pixels. Early super-resolution algorithms used a single input image and generated a single output image on a finer, or higher-resolution, grid. In these methods, prior knowledge about the spatial extent of the objects in an image and analytic continuation theory are used to extrapolate the spectrum of the image [32]. More recent super-resolution methods use multiple low-resolution input images to generate either a single high-resolution image or, in the case of video super-resolution, multiple high-resolution video frames. These recent super-resolution methods are also called *super-resolution image reconstruction* algorithms, and are the starting point for the multi-angle resolution enhancement technique explored in this dissertation. Reviews of approaches for super-resolution using multiple images are given in [5–7].

Super-resolution image reconstruction methods are divided into two approaches: frequency domain methods and spatial domain methods. Frequency domain methods are limited to global translational shifts between frames and spatially-invariant blurring. Consequently, they cannot be used for combining multi-angle remote sensing data, since the multi-angle frames may be rotated with respect to one another, may have perspective distortion, and may have irregular sample spacing. Spatial domain methods are much more flexible, allowing sophisticated imaging models to

be used. Three main categories of spatial domain resolution enhancement are interpolative, probabilistic, and set-theoretic methods. Each of these spatial domain methods is reviewed in the following sections.

2.7 Interpolative Image Resolution Enhancement

Interpolative image reconstruction techniques take the simple approach of aligning or registering multiple low-resolution images followed by interpolating the values from each image onto a high-resolution grid [7]. Multiple images are used rather than a single image, as is the case for the standard image interpolation discussed in Sect. 2.4.

Interpolative reconstruction techniques include shift-and-add and interlacing [33]. The shift-and-add method is a simplistic method of combining multiple images. Pixel values are mapped, or shifted, to their proper location in a high-resolution grid, then added to the grid values without modification. Interlacing is another linear method of merging images where the input pixels are interleaved to form a single output image. The positions of the pixel centers in the input images determine the order of interleaving: if image “a” contains pixels shifted one-half of a pixel to the left of those in image “b”, the output pixels would be arranged as “ababab”. Neither method attempts to remove the effects of blur. Variable-Pixel Linear Reconstruction, also known as Drizzle [33], is an algorithm that linearly reconstructs a high-resolution image from a set of undersampled images. It has been

applied to the problem of reconstructing images from the wide field cameras (WFCs) of the Hubble Space Telescope (HST). Interpolation of nonuniformly-spaced data samples from several images has been considered. Sauer and Allebach [34] interpolate between irregular samples but do not account for system PSF blur. Chen and Allebach [25] study the relation of mean squared error to the spacing of irregular samples. Scambos *et al.* [35] use a linear technique called data cumulation to increase the resolution of AVHRR data by averaging multiple images onto a finer sampling grid. Like other resolution enhancement algorithms, accurate coregistration, or alignment, of the images is required; data cumulation requires coregistration accuracy of better than 0.2 pixels.

2.8 Probabilistic Image Resolution Enhancement

A popular approach for super-resolution image reconstruction uses Bayesian estimation methods, such as the maximum likelihood (ML) and the maximum a priori (MAP) methods [5–7]. The Bayesian approach has the advantages of giving a unique solution subject to its constraints, and using *a priori* information to constrain the HR estimate. In the MAP method, the goal is to find the HR estimate $\hat{f}$ of the object or scene f that maximizes the *a posteriori* probability distribution function (PDF) $P(f|g_k)$,

$$\hat{f} = \arg \max_f P(f|g_1, g_2, \dots, g_N), \quad (2.5)$$

or, using Bayes' theorem,

$$\hat{f} = \arg \max_f [\ln P(g_1, g_2, \dots, g_N | f) + \ln P(f)], \quad (2.6)$$

where each g_k , $k = 1, \dots, N$, is the k -th observed LR frame, $P(f)$ is the image model, which defines the statistical correlation between neighboring pixels, and $P(g|f)$ is the likelihood function determined by the PDF of the noise in the image. Typically, Gaussian noise is assumed and a Markov random field (MRF) image model is used [5]. A few researchers have used Bayesian methods for enhancing the resolution of remotely-sensed images. A Bayesian maximum posterior estimation (BMPE) method was applied to AVHRR imagery in [36]. This work assumed that the observed surfaces were Lambertian and that there was no atmosphere, but did remove the effect of the AVHRR's PSF. A Bayesian approach was also used by Cheeseman *et al.* for the super-resolution of images from the Mars Pathfinder mission [37]. However, their paper showed that a Gaussian neighbor correlation prior is not suitable for Landsat imagery due to the high energy in the tails of the distribution. They concluded that "individual pixels in Earth imagery can differ substantially from their neighbors, e.g., a road traversing ground" [37], meaning that Bayesian resolution enhancement can oversmooth the HR estimate when applied to remotely-sensed images. Because the goal of this dissertation is to enhance edge features in remote sensing imagery, Bayesian resolution enhancement methods were therefore not chosen for further study.

2.9 Set Theoretic Image Resolution Enhancement: The Projection Onto Convex Sets (POCS) Algorithm

Set theoretic image resolution enhancement is a popular alternative to the Bayesian resolution enhancement approach. The most widely used algorithm of this type is the projection onto convex sets (POCS) algorithm. The POCS algorithm iteratively estimates a high resolution image from a set of low resolution images by performing simultaneous interpolation and restoration. Thus, POCS both increases the size of the image and removes the effects of blur due to the system PSF. The POCS method has many advantages for the resolution enhancement of images [38], including the flexible incorporation of prior knowledge, the ability to acquire the LR frames using any detector or scanning geometries including nonuniform sampling, the capability to compensate for different amounts and types of blur in each LR frame, and the ability to combine LR frames with different pixel sizes. The ability to input satellite images with different GSD's was an important factor for selecting POCS for the resolution enhancement. In addition, the POCS algorithm may be used with other optimization methods, such as the statistical ML and MAP approaches, resulting in powerful hybrid methods. Hybrid methods will not be explored in this dissertation, but would be a good starting point for future research. The POCS algorithm does have the drawback of slow convergence, but continues to be the most popular implementation of convex set theoretic image recovery [39]. Another algorithm, called

extrapolated method of parallel subgradient projections (EMOPSP), uses approximate projections and applies constraints in parallel to speed convergence [39].

Convex set theoretic methods for resolution enhancement have been around for several decades. In an early paper that introduced POCS to the engineering community, Youla and Webb [40] described an iterative image restoration method based on convex projections. In contrast to earlier algorithms by Papoulis and Gerchberg, which are based on linear image reconstruction concepts, the Youla-Webb algorithm allowed multiple nonlinear constraints to be applied. Sezan and Stark [41] then applied Youla and Webb’s algorithm to an example, in the companion paper to Ref. [40]. Lent and Tuy describe a POCS-based image reconstruction algorithm that is similar to that of Youla and Webb [42]. They incorporate the ideas of Gerchberg, Papoulis, and Youla [43], but their paper appeared before, and independently of, Youla and Webb’s nonlinear restoration paper. Their algorithm is iterative and also allows a priori constraints. More recently, Stark and Oskoui [38] applied POCS to the recovery of tomographic images, and this paper led to the work of Tekalp, Ozkan, and Sezan, who extended POCS to handle linear-shift-varying (LSV) blurs [44, 45]. Their algorithm implementation forms the main multi-angle resolution enhancement algorithm of this dissertation. Yeh and Stark have also developed iterative and one-step POCS for nonuniform samples [46]. Granrath and Lersch [47] used POCS for

the fusion of remote sensing imagery, but they used a 2D affine transform assumption; for multi-angle remote sensing imagery, a projective transform is needed rather than an affine transform.

The POCS algorithm uses prior knowledge about the imaging system to impose constraints on a high-resolution (HR) estimate of the original scene. The use of *a priori* knowledge helps the algorithm converge to a reasonable solution. Constraint sets may be formed for data consistency, energy bounds, amplitude bounds, spatial support bounds, etc. More precisely, each constraint defines a closed convex set C , which, for image reconstruction, is a set of images with a particular property. For example, C could be defined as the set of all objects in continuous space that could have resulted in one particular discretized LR image: if a red car and an orange car are imaged with a panchromatic sensor, the LR image could contain the exact same DN pixel values in each case. The object f is known *a priori* to belong to the intersection C_s of m closed convex sets $C_1, C_2, \dots, C_m$,

$$C_s = \bigcap_{\alpha=1}^m C_{\alpha}, \quad (2.7)$$

where C_s is found by iteratively computing projections onto the convex sets (thus the name POCS):

$$f_{n+1} = P_m P_{m-1} \dots P_2 P_1 f_n. \quad (2.8)$$

The projection operator P_i maps the current estimate f to the closest point in the set C_i . Fig. 2.3 illustrates the POCS method, closely following a figure from Ref. [48]. One important constraint used in POCS ensures data consistency – that is, the HR

Figure 2.3: The POCS algorithm for two constraint sets, shown converging to a solution f in the intersection set C_s .

estimate, when blurred and downsampled, must be consistent with the observed LR frames. This constraint is defined as

$$C_D = \{f : |r| \leq \delta\}, \quad (2.9)$$

where the residual r is the difference between a LR pixel value and a blurred region in the HR estimate

$$r(i, j) \doteq g(i, j) - \sum_k \sum_l f_n(k, l) h(i, j; k, l), \quad (2.10)$$

and $\delta = c\sigma_v$, the confidence of the user in the observation for a noise standard deviation of σ_v , with the constant $c \geq 0$ found using a statistical confidence bound [44]. The projection of f onto the constraint set C_D is then

$$f_{n+1} = P_D f_n = \begin{cases} f_n + h(r - \delta) / \sum_k \sum_l h^2 & \text{if } r > \delta \\ f_n & \text{if } -\delta < r < \delta \\ f_n + h(r + \delta) / \sum_k \sum_l h^2 & \text{if } r < -\delta \end{cases} \quad (2.11)$$

The POCS image reconstruction method using only the data consistency constraint may be summarized in the procedure shown in Figs. 2.4 and 2.5.

2.10 Image Registration

One issue that has not yet been addressed is image registration in the context of resolution enhancement. Image registration methods compute the relative motion or shifts between two images in order to align them to one another. Resolution enhancement algorithms must register the LR frames to one another in order to

- Align (register) the LR images using known translation, rotation, and skew
- Until estimate f has converged:
 - For each pixel in each LR frame:
 - * Find the non-integer location of the pixel center in the HR estimate
 - * Apply blur to a neighborhood (window) of HR pixels corresponding to the estimated or known point spread function (PSF) of that LR frame
 - * Subtract the average of the blurred region in the HR image from the LR pixel to find the residual r
 - * Compute the new HR image values within the PSF window by adding the residual r multiplied by the PSF

Figure 2.4: The POCS algorithm using the data consistency constraint.

Figure 2.5: Mapping the LR pixel to the HR estimate and computing the residual from the PSF applied to a local neighborhood.

determine the location of each LR data point in the HR output grid to subpixel accuracy. If the registration parameters are not correct, resolution enhancement algorithms will give poor results. Misregistration and its effect on change detection are discussed in several papers [30, 49, 50]. In [50], the authors found that a change detection error of ten percent requires the registration between the images to be accurate to within one-fifth of a pixel.

For registration of remotely-sensed imagery, registration may be achieved by determining a given subpixel location in each image's sampling grid that corresponds to the same location on the surface of the earth. If the images are co-registered to each other, and also are aligned to absolute latitude and longitude coordinates, they are said to be geo-registered. Multispectral sensors such as the MTI require co-registration of the images for each spectral band because each band image is formed by a separate line detector [51]. Image-to-image registration is often done using ground control points or cross-correlation [52]. Cross-correlation methods are simple, but they require images with the same geometry (i.e., no rotation or skew). The availability of the same geometry is rare in remotely-sensed imagery because the imaging system is in motion and very far from the object being imaged. Instead, the most common techniques to register satellite images are ground control point (GCP) methods. Ground control points (GCP's) are features in each image that match each other. Typically, these include road intersections or other features that can be precisely located in each image. GCP's are chosen by a user or by using an

automated technique. User selection of ground control points is labor-intensive, but it gives very accurate results. First, matching GCP's are selected in each image. Then, a mapping function is computed that specifies how to warp one image onto the other. Automated methods for selecting GCP's are more error prone. Other, more advanced automated registration algorithms exist, using a variety of image features and iterative methods to achieve subpixel registration.

Although image registration is critical for resolution enhancement, it is not studied in this dissertation. Instead, simulated imagery is used so that the registration parameters are known absolutely. Other resolution enhancement research has addressed misregistration issues as well as incorporating image registration within the resolution enhancement algorithm.

CHAPTER 3

SIMULATING MULTI-ANGLE IMAGERY

3.1 Image Formation

To simulate imagery for input into our resolution enhancement algorithm, a model of the image formation process for multi-angle, remotely-sensed imagery is needed. Our model must account for the optics of the imaging system, the changing view angle, and the sampling process of the detector array. We discuss each of these components in the following sections.

3.2 Modeling the Optics

In its most basic form, an optical system consists of four components: an object, a propagation medium, an optical system, and an image. Energy in the form of light travels from an object f , through a propagation medium and optical system, and forms an image g , as shown in Fig. 3.1. The quality of the image is determined by the optical wave properties of each component of the system.

Several simplifying assumptions are used to make the implementation of our optical system model tractable. First, we assume that objects are imaged using quasi-monochromatic incoherent light. Second, we assume an aberration-free, diffraction-limited optical system. The image is assumed to be z-coordinate independent. This

Figure 3.1: Optical imaging system

means the image $g(x, y, z)$ is approximately equal to $g(x, y)$. We assume the image is formed in the Fraunhofer (far field) region [18, 53],

$$z \gg \frac{\pi R_o^2}{\lambda}, \quad (3.1)$$

where z is the distance from the optical system's limiting aperture to the detector, and R_o is the radial extent of the object at the diffracting aperture. The exact nature of the aperture is described later, but for the time being may be treated as a telescope lens in front of a focal plane comprised of a 2D CCD array. These simplifications result in a linear, shift-invariant (LSI) imaging model. The wavelength-dependent scaling between the aperture and image plane coordinate systems is ignored for simplicity in the following discussion. Since we assume spatially incoherent object illumination, our optical system model is linear in intensity rather than amplitude

[18, 53]. Thus the incoherent system impulse response is the squared magnitude of the coherent system impulse response. It is real-valued and nonnegative. The system impulse response for an optical system is often called the point spread function (PSF). The intensity image, g , of an object f formed by an incoherent, LSI optical system with a PSF h may be illustrated as shown in Fig. 3.2. The PSF may be

Figure 3.2: Linear, shift-invariant imaging system model

thought of as a two-dimensional lowpass filter and will be described more precisely below. The imaging system may be described equivalently as a two-dimensional spatial convolution of the object f with the PSF h ,

$$g(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\xi, \eta) h(x - \xi, y - \eta) d\xi d\eta \quad (3.2)$$

$$= (h * f)(x, y) \quad (3.3)$$

where x, y are the coordinates in the image plane and ξ, η are the coordinates in the object plane.

It is useful to describe the optical system in terms of its frequency response, because the sharpness of edges and fine detail in a scene correspond to high frequencies in the Fourier domain. A brief description of an optical system from a Fourier optics viewpoint is now provided.

The two-dimensional Fourier transform of a function s is defined as

$$\mathcal{F}\{s(x, y)\} = S(u, v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} s(x, y) e^{-j2\pi(ux+vy)} dx dy. \quad (3.4)$$

Taking the Fourier transform of Eq. 3.3, and after some rearranging of terms, we can express the incoherent optical system response in the frequency domain as

$$G(u, v) = H(u, v)F(u, v), \quad (3.5)$$

where F is the Fourier transform of the object, G is the Fourier transform of the image, and $H(u, v)$ is the incoherent optical transfer function (OTF) of the system [18, 32]. The OTF governs how spatial frequencies are preserved from the object to the image. Specifically, the incoherent OTF is defined as the normalized complex autocorrelation of either the aperture stop or the exit pupil, with a scaling factor [18]. For our purposes, it is sufficient to define an aperture function, $a(x, y)$, that could be a physically real pupil or a limiting aperture within the optical system. This limiting aperture restricts the total amount of light entering the imaging system [32]. Inside the aperture, $a(x, y) = 1$, while outside the aperture, $a(x, y) = 0$ and no light can pass through the system. In this case, the OTF is simply

$$H(u, v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} a(x, y) a(x + u, y + v) dx dy, \quad (3.6)$$

where the scaling factor has been neglected between the x, y space coordinates and the u, v spatial frequency coordinates [32]. The OTF is normalized such that $H(0, 0) = 1$. The maximum of the OTF occurs at the origin since it is found by an autocorrelation operation. An important point to make is that the OTF $H(u, v)$

goes to zero outside of a region of support, again, from properties of the autocorrelation. Therefore, spatial frequencies outside of the region where $H(u, v) > 0$ will not be present in the image that is output from the optical system. The blur due to the limiting aperture, and thus the OTF, fundamentally limits the resolution or amount of detail that may be seen in the image. The spatial frequency at which the OTF goes to zero is called the optical cutoff frequency, f_c . It is given by

$$f_c = \frac{D}{\lambda l} \quad (3.7)$$

where D is the aperture diameter, λ is the wavelength of the light, and l is the focal length of the optical system.

The aperture function we will use to generate blurred imagery is a simple circular pupil [53], $a(x, y)$, of radius r ,

$$a(x, y) = \text{circ} \left(\frac{\sqrt{x^2 + y^2}}{r} \right), \quad (3.8)$$

and is shown in Fig. 3.3. The incoherent OTF, or complex autocorrelation of the aperture a , is given by

$$H_o(u, v) = \begin{cases} \frac{2}{\pi} \left[\cos^{-1} \left(\frac{f}{f_c} \right) - \frac{f}{f_c} \sqrt{1 - \left(\frac{f}{f_c} \right)^2} \right] & f < f_c \\ 0 & \text{otherwise} \end{cases} \quad (3.9)$$

where $f = \sqrt{u^2 + v^2}$ is the radial distance in the frequency plane [53]. The OTF is shown in Fig. 3.4.

Figure 3.3: Circular aperture function

Figure 3.4: Incoherent OTF, $H(u, v)$, for a circular aperture

To simulate diffraction-limited image blur due to the optical system, we first compute the two-dimensional Fourier transform of a high resolution “object” scene to obtain its spectrum. A standard FFT is used in the implementation. A circular aperture size is selected and the corresponding OTF is calculated. Next, the object spectrum is multiplied by the OTF, which removes the high frequencies present in the high-resolution image. The output of this step is a blurred image with the same number of pixels as the high resolution image. An example of an image blurred by diffraction effects by a circular aperture is shown in Fig. 3.5. For better visibility of the high frequencies, the object and image spectra are displayed using a $\ln(1 + |\cdot|^2)$ compression on the scaling.

Figure 3.5: High resolution object scene blurred by a circular aperture (spectra shown scaled with logarithmic compression).

With the generic optical system model in place, we must now incorporate additional knowledge of the satellite into our multi-angle imaging system model. To generate the multi-angled frames that would be viewed by a satellite-based sensor, two additional steps are required. First, the blurred image has a projective transform applied to it to simulate an off-nadir view angle. Then, the image is subsampled to model the detector array of the satellite system. These components of the system are presented next.

3.3 Modeling the Changing View Angle Between Frames

Between frames, we assume that the satellite carrying our imaging system has moved. Satellite motion can be very complex, but a simple model will be implemented to study the most important issue for multi-angle resolution enhancement problem: the view angle. Other issues, such as terrain, slope, elevation, and curvature of the Earth, are important, but are secondary to the issue of the increasing view angle from nadir and the subsequent increase in the pixel size due to the increased path length to the imaged scene as the angle increases.

It takes the MTI satellite 4.5 seconds to acquire a 12 km by 12 km image for all 16 spectral bands. The velocity of the satellite is 7 km/sec, thus the satellite travels approximately 31.5 km while acquiring a single image. The change in angle between the beginning of acquisition and the end of acquisition results in a change in the size of the projection of the detector line. The changing view angle (perspective)

between nadir and the satellite with respect to the location of a feature on the ground may be modeled with a projective transform. The simplified geometry of an off-nadir image formed by a pushbroom sensor is shown in Fig. 3.6. The off-nadir field of view (FOV) in the cross-track direction, $\text{FOV}_{\text{O,C}}$, or swath width, is determined by the cross-track extent of the linear detector array projected onto the ground. Over $\Delta t = t_2 - t_1 = 4.5$ sec, the path length increases from l_1 to l_2 , and the swath width becomes smaller. The off-nadir FOV in the along track direction, $\text{FOV}_{\text{O,A}}$, is determined by the image acquisition time and the off-nadir pointing angle at the midpoint of image acquisition θ_{ave} . Compared to the nadir along-track FOV, it is reduced by a factor of cosine squared (just as for the along-track off-nadir GSD shown previously in Fig. 1.4). Using the homogeneous coordinate system to perform two-dimensional coordinate transforms, the projective transform is given by [54]:

$$[x', y', w'] = [u, v, w] \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}. \quad (3.10)$$

To model an off-nadir image with a projective transform, the forward mapping is applied to convert the u, v input coordinates to x, y output coordinates, given by

$$x = \frac{x'}{w'} = \frac{a_{11}u + a_{12}v + a_{13}}{a_{31}u + a_{32}v + a_{33}} \quad (3.11)$$

$$y = \frac{y'}{w'} = \frac{a_{21}u + a_{22}v + a_{23}}{a_{31}u + a_{32}v + a_{33}}. \quad (3.12)$$

SIDE VIEW

Figure 3.6: Off-nadir geometry for a single band.

An example of projective distortion due to a satellite viewing a scene from nadir and off-nadir is shown in Fig. 3.7. The off-nadir image appears scaled, but not much

Figure 3.7: Nadir and off-nadir image at 45° simulated using a projective transform with an orbital height of 575 km.

keystoning is visible because the distance from the sensor to the target (575 km for the MTI at nadir) is much larger than the extent of the image acquired (12 km by 12 km for the MTI).

3.4 Modeling the Detector Array Subsampling

The detector array effectively discretizes our image. This may be modeled by downsampling the blurred and transformed images to a grid with fewer pixels in each dimension. The subsampling process can introduce aliasing into the images. Recall from Sect. 3.2 that the optics of the system have an impulse response, or

PSF_{optics}. If a point source is imaged by this system, it forms a diffraction pattern in the far field that consists of bright concentric rings called the Airy pattern [53,55]. The diameter of the central lobe is given by

$$d_{Airy} = 2.44 \frac{\lambda f}{D}, \quad (3.13)$$

where λ is the wavelength of the point source, f is the focal length (the distance from the lens to the focal plane), and D is the diameter of the aperture or lens. The detectors located at the focal plane also have a PSF,

$$\text{PSF}_{detector}(x, y) = \text{rect}\left(\frac{x}{d_x}\right) \text{rect}\left(\frac{y}{d_y}\right) \quad (3.14)$$

where d_x and d_y are the sizes of a rectangular detector in the x and the y directions, respectively. For most detectors, the detector shape is square, or $d_{det} = d_x = d_y$. Assuming a 100% fill-factor for the detector array, when $d_{Airy} > d_{det}$, the system is called *optics-limited* [55]. When $d_{Airy} < d_{det}$, it is called *detector-limited*. These terms arise because the system PSF is given by the convolution of the optical and the detector PSF's,

$$\text{PSF}_{system} = \text{PSF}_{optics} * \text{PSF}_{detector}, \quad (3.15)$$

and the system OTF is given by the multiplication of the component OTF's,

$$\text{OTF}_{system} = \text{OTF}_{optics} \text{OTF}_{detector}. \quad (3.16)$$

The cutoff frequency of the optics OTF versus the detector OTF determines the whether aliasing is present. If high frequencies are allowed through the optics, but

the detectors are not small enough, the high frequencies are aliased to low frequencies in the discretized output image.

It is important to understand the effects of aliasing when applying resolution enhancement algorithms to multispectral imagery because the degree of aliasing present varies with wavelength. For a system like the MTI, the same optics are used for both the visible and the IR bands, while the size of the detectors changes, resulting in more aliasing at the shorter wavelengths. For the MTI, $D = 36\text{cm}$ and $f = 125\text{cm}$. In band A, $\lambda \approx 485\text{nm}$, so $d_{\text{Airy}} \approx 4.1\mu\text{m}$, much smaller than $d_{\text{det}} = 12.4\mu\text{m}$. The system is detector-limited in band A. In the IR bands, $\lambda \approx 10\mu\text{m}$, and $d_{\text{Airy}} \approx 84.7\mu\text{m}$, about twice the value of $d_{\text{det}} = 49.6\mu\text{m}$, meaning the IR bands for the MTI are optics-limited.

An example of an image after downsampling is shown in Fig. 3.8. Compared to the blurred image, the pixel size of the downsampled image is four times larger in each dimension, making high frequency detail much more difficult to see after sampling.

3.5 The Elliptical Gaussian System PSF Model

The POCS algorithm requires knowledge of the system PSF. With the added complication of off-nadir frames, the known or estimated PSF must be warped; the projective transform model requires a mapping of the system PSF from every pixel in each LR frame to the HR estimate, resulting in a distorted PSF in the HR grid.

Figure 3.8: Blurred image vs. blurred, 4X downsampled image

The computation of the projected system PSF can be time consuming [6]. However, it is possible to use an approximate mapping of the PSF using an affine transform rather than a projective transform and keep the processing time reasonable. For off-nadir images simulated using the parameters of the MTI sensor, the primary transformation of the off-nadir image is a change in scale; the perspective keystoneing is small due to the very large distance from the satellite to the ground. Therefore, the affine transform is reasonable for mapping the PSF of a satellite sensor from the off-nadir LR frames to the HR estimate grid. Using the affine mapping, the projected PSF will be the same for every pixel in a given LR frame, thus reducing the computational time considerably.

First, a model for the system PSF in a nadir viewing case must be selected. Two-dimensional Gaussian functions, both circular and elliptical, have been used previously to model the system PSF of a satellite. Moreno and Media [20] show

that an elliptical Gaussian function is best for approximating the system PSF of the AVHRR instrument. Baldwin et al. [36] use a circular Gaussian function with the assumption that it is an adequate approximation for angles less than 20 degrees, and cite Oleson et al. [56] for the justification of using a Gaussian function to approximate an Airy disk. Following the justification in Ref. [20], a 2D Gaussian function is used to approximate the system PSF in this dissertation. The Gaussian PSF is circularly symmetric at nadir, assuming the optics do not have distortions. Mapping the PSF from a given off-nadir LR frame to the HR estimate grid with an affine transform results in an elliptical Gaussian PSF, given by

$$\text{PSF}(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-x^2/2\sigma_x^2} e^{-y^2/2\sigma_y^2} \quad (3.17)$$

where σ_x and σ_y are determined by scaling the circularly symmetric nadir PSF of width σ by a cosine or a cosine-squared factor of the off-nadir look angle θ , so that

$$\sigma_x = \frac{\sigma}{\cos \theta} \quad (3.18)$$

in the cross-track direction and

$$\sigma_y = \frac{\sigma}{\cos^2 \theta} \quad (3.19)$$

in the along-track direction. The PSF is normalized so that the area under the PSF is constant. This ensures that the weighting during the blur step of the POCS algorithm (see Fig. 2.4) is correct.

CHAPTER 4

VALIDATION OF THE POCS ALGORITHM

4.1 Validation Overview

In this chapter, multi-angle imagery is simulated using the sensor model of Ch. 3 and the POCS resolution enhancement algorithm of Sect. 2.9 is applied to the simulated data sets. The validation of POCS for use with remotely-sensed multi-angle imagery covers several areas. First, a description of how the algorithm will be quantitatively tested is needed; image quality metrics are defined in Sect. 4.2. Aliasing is an important issue to examine when using resolution enhancement algorithms for remotely-sensed imagery. Therefore, a simulated test image with varying amounts of aliasing is used to measure the performance of the POCS algorithm with aliased and non-aliased images in Sect. 4.3. In Sect. 4.4, the POCS algorithm is applied to simulated two-look images. Using images at off-nadir view angles is a challenge for the algorithm due to the irregular sample spacing of the data; a brief analysis of the effect of sample spacing on POCS performance is provided in Sect. 4.5. Resolution enhancement results are extended to multiple looks in Sect. 4.6. The performance of POCS using symmetric three-look images is discussed in Sect. 4.7, and aliasing in three-look imagery is examined in Sect. 4.8. In Sect. 4.9, the POCS algorithm is applied to unique imagery from a multispectral microscope in order to show how

the POCS resolution enhancement algorithm may be used to improve multispectral data.

4.2 Error Metrics

One of the challenges of comparing resolution enhancement algorithms is the paucity of quantitative results in the literature; many papers use only a visual comparison of imagery before and after resolution enhancement. To truly measure the performance of resolution enhancement algorithms, quantitative image quality metrics are needed. Two frequently used image error metrics are the mean squared error (MSE) and the peak signal-to-noise ratio (PSNR). These error metrics do not always correspond well to a subjective visual comparison between images, but are widely used because they provide an objective measure to compare image processing methods. The MSE between two discrete images of size $M \times N$ is given by

$$\text{MSE}(f, \tilde{f}) = \frac{1}{MN} \sum_{n=1}^N \sum_{m=1}^M [f(m, n) - \tilde{f}(m, n)]^2, \quad (4.1)$$

where f is the desired object and $\tilde{f}$ is the resolution-enhanced image. The MSE is dependent on intensity scaling (the number of bits used to store each pixel value), so the PSNR metric is often used to avoid this problem. The PSNR (in dB) is given by

$$\text{PSNR}(f, \tilde{f}) = 10 \log_{10} \left(\frac{[\max(f)]^2}{\text{MSE}} \right) \quad (4.2)$$

$$= 10 \log_{10} \left(\frac{[\max(f)]^2}{\frac{1}{MN} \sum_{n=1}^N \sum_{m=1}^M [f(m, n) - \tilde{f}(m, n)]^2} \right), \quad (4.3)$$

where $\max$ is the maximum pixel value possible, e.g., $2^k - 1$ for a k -bit image. The SNR improvement, or ISNR (measured in dB), is a useful metric for image restoration [17]. It is given by

$$\text{ISNR}(f, \tilde{f}, g) = 10 \log_{10} \left(\frac{\frac{1}{MN} \sum_{n=1}^N \sum_{m=1}^M [f(m, n) - g(m, n)]^2}{\frac{1}{MN} \sum_{n=1}^N \sum_{m=1}^M [f(m, n) - \tilde{f}(m, n)]^2} \right). \quad (4.4)$$

It measures the distance between the original scene f and a restored image $\tilde{f}$ as well as the distance between the original scene f and the degraded image g . This metric assumes that the original, degraded, and restored images are the same size. Since the degraded images here are the LR frames, which are at a lower resolution than that of the original and HR estimate, some modification to the ISNR metric must be made in order use it to measure resolution enhancement performance. A baseline “degraded” image g may be formed by interpolating (i.e., bilinear interpolation) the nadir LR frame to the same size as the original image and the HR estimate. Then, the ISNR will provide a measure of how much better the restored image is compared to the interpolation of just one LR frame, or roughly, how much additional information has been gained from the off-nadir frames. Obviously, when real imagery is used rather than simulated imagery, the ISNR cannot be computed since the “original” image f is not known.

In addition to the above objective error metrics, simple visual differences between images and their spectra may be used to observe the algorithm performance. A difference image between the original high resolution object scene f and the resolution-enhanced image $\tilde{f}$ is a useful qualitative measure of how the algorithm performs. The difference image is simply

$$d = |f - \tilde{f}|. \quad (4.5)$$

Areas where convergence is more difficult, such as along edges, may be examined using this visual measure of error, since not only the magnitude of the error is given, but the locations of errors are given as well.

Finally, comparing the spectra of low resolution images to the spectrum of the original high resolution image and to the spectrum of the resolution-enhanced image can show improvement of high resolution detail by the presence of spectrum components beyond the cutoff frequency of the low resolution images. It is expected that a resolution enhancement algorithm would restore high frequencies present in the original high resolution image that have been lost through the imaging process. The appearance of high frequency components in the restored image's spectrum that do not match the original object's spectrum would indicate undesirable ringing artifacts and noise amplification.

4.3 The Effect of Aliasing: Recreating Points and Edges

Aliasing occurs in most imaging systems [55], as was discussed in Sect. 3.4. Aliasing is usually implicitly assumed to exist when generating subsampled frames as test data for resolution enhancement algorithms [44, 57]. However, the effect of aliasing has not been amply treated in the literature; no experiments or simulations to study the issue in detail have been done. Therefore, some simulations of super-resolution image reconstruction with varying amounts of aliasing were performed to quantify this behavior.

To demonstrate the ability of POCS to enhance the resolution of aliased images, a simple test data set was formed. The test pattern contains both lines and points, features that show how well the algorithm can reconstruct point sources and how well it can localize edges. The test image is 64×64 pixels in size, and is shown in Fig. 4.1. Sixteen low-resolution (LR) input frames, each 16×16 pixels in size, may be formed by decimating the test pattern. The decimation step must be done carefully because it has an important effect on the amount of aliasing in each LR frame, and, as will be shown, on the super-resolution results. In some earlier resolution enhancement experiments [44, 57], the simulated LR frames were generated from the input test image by first blurring the test image with a neighborhood operator (either a 4×4 uniform or Gaussian kernel), then selecting every fourth pixel to form sixteen distinct LR frames. This method does not allow the user to easily measure the effects of aliasing on the resulting HR estimate because it does not give the

Figure 4.1: Input test pattern containing lines and points

user enough control to accurately model the behavior of a specific imaging system, as described in Ch. 3. Carefully modeling the optics, detector array, and viewing geometry is important for studying the applicability of resolution enhancement algorithms to sets of low-resolution imagery taken at different sensor pointing angles. Thus, in the experiments performed for this dissertation, blurring was done with a modeled circular aperture to remove all frequency components above a well-defined spatial cutoff frequency, f_c . By varying f_c , the effect of aliasing on the resolution enhancement performance may be studied for specific remote sensing sensor configurations.

Figure 4.2 illustrates the aliasing issue, showing the spectrum of the test pattern blurred with both the 4×4 uniform kernel and the 4×4 Gaussian kernel. To correctly model a set of 16×16 LR frames without aliasing, the spatial cutoff frequency, f_c , required is shown by a white circle. The spectrum in both cases

Figure 4.2: The spectrum of a test pattern blurred by a 4×4 uniform kernel (left) and by a 4×4 Gaussian kernel with $\sigma = 1.5$ (right), with the Nyquist cutoff frequency represented by the white circles.

shows energy at frequencies above the Nyquist frequency, meaning that test pattern will contain aliasing artifacts. The spectrum for the Gaussian kernel has moderate levels of energy at frequencies nearly double the Nyquist frequency. The spectrum for the uniform kernel contains very high frequencies compared to the Nyquist cutoff frequency. The uniform blur kernel does not accurately model a real imaging system. The Gaussian kernel is more accurate than the uniform kernel, but it is difficult to relate the kernel size to a system's physical parameters such as mirror size or detector size.

It is important to note that a few other researchers have taken the more rigorous Fourier-optics-based approach in their resolution enhancement simulations. As mentioned in Sect. 3.5, Baldwin et al. [36] used a Gaussian model of the AVHRR

PSF in their simulations. However, the effects of the optics versus the detector size on the resolution enhancement algorithm were not studied; their Gaussian PSF model combined the optics PSF and the detector PSF. Thus, their results were specific to the AVHRR instrument. Hardie et al. [58] modeled a system PSF for an infrared imaging system. The system was detector-limited (aliased) and the resolution enhancement results are specific to that instrument. Borman and Stevenson [6] modeled the PSF of an aliased camera system for the resolution enhancement of video.

The spectrum of the HR test pattern bandlimited to the Nyquist frequency is shown in Fig. 4.3, along with the spectrum of a LR frame after downsampling that shows the preservation of the spectral information without aliasing. Spectra are displayed with logarithmic compression to show detail. The complete set of sixteen Nyquist-bandlimited LR images is shown in Fig. 4.4. In this experiment, the goal is to increase the resolution by four in both the x and the y directions. In principle, for a spatial resolution increase of N , N^2 low-resolution frames are needed, each with an N th of a pixel shift with respect to the other frames. Thus, we create sixteen frames, each of dimension 16×16 , with one-fourth pixel shifts. Once the LR frames have been simulated, they are used to test the performance of the POCS resolution enhancement algorithm.

Figure 4.3: Spectrum of the test pattern after bandlimiting to the Nyquist frequency (upper left) and spectrum of a LR frame (upper right), corresponding blurred image (lower left), and blurred and downsampled image (lower right).

Figure 4.4: Sixteen unique LR frames formed by bandlimiting to the Nyquist frequency, $f_c = f_N$, and downsampling.

Borrowing terminology from machine learning, an *epoch* is defined as the presentation of all of the LR frames to the resolution enhancement algorithm. An *iteration* is the presentation of all pixels in a single LR frame to the algorithm. The Nyquist-limited simulation was run with the 16 LR frames over 40 epochs, or $16 \times 40 = 640$ iterations. This means the algorithm saw every LR frame 40 times before it was stopped, ensuring time for its convergence. The elliptical Gaussian function with $\sigma = 3.5$ pixels was used to estimate the system PSF. To provide an initial HR estimate, a single LR frame was upsampled using bicubic interpolation. The interpolated LR frame is shown in Fig. 4.5. The estimated HR image after one epoch is shown in Fig. 4.6, after ten epochs in Fig. 4.7, and after 40 epochs in Fig. 4.8.

Figure 4.5: Bicubic interpolation of one LR frame containing lines and points.

Figure 4.6: The HR estimate after running POCS for 1 epoch, $f_c = f_N$.

Figure 4.7: The HR estimate after running POCS for 10 epochs, $f_c = f_N$.

Figure 4.8: The HR estimate after running POCS for 40 epochs, $f_c = f_N$.

It is interesting to compare the interpolated LR frame to the result obtained by running POCS on multiple frames. The pixel size is smaller in the upsampled image, but interpolation alone does not remove the blur, and the point sources are still not visible. The HR estimate shows more detail after only one epoch, with the point sources now visible and the width of the lines reduced compared to the interpolated initial image. After 10 epochs, the image has been restored with good visual quality, though not perfect. After 40 epochs, ringing is apparent in the image. Some POCS implementations use an energy constraint to reduce such ringing at the edges. Nonetheless, the resulting HR image demonstrates the ability of POCS to enhance the resolution of a Nyquist-bandlimited image with a large blur relative to the size of a feature. The point sources are nearly restored to their original 1×1 pixel size. A plot of the ISNR after 200 epochs for the Nyquist-bandlimited case, $f_c = f_N$, is shown in Fig. 4.9. Even though the ISNR is increasing, meaning that the algorithm has not converged, the visual quality is not improving due to ringing artifacts. Thus, stopping criteria for POCS are not easy to define. A visual inspection of the algorithm's progress may be needed to stop the convergence at a suitable point; when real rather than simulated data is used, the original image is not available for comparison, and the quantitative ISNR metric cannot be computed. It is evident that stopping criteria are an important aspect of resolution enhancement algorithms.

Figure 4.9: The ISNR for the Nyquist-bandlimited test pattern, $f_c = f_N$, for 200 epochs.

Next, a case with aliasing present is examined. The limiting aperture is set to be twice as large as before. The spectrum of the HR test pattern for this case and the downsampled LR image spectrum are shown in Fig. 4.10. The spectrum is truncated during downsampling because $f_c > f_N$, resulting in aliased LR frames.

Figure 4.10: Spectrum of test pattern after bandlimiting to the twice the Nyquist frequency, $f_c = 2f_N$, (upper left) and spectrum of LR frame (upper right), corresponding blurred image (lower left), and blurred and downsampled image (lower right).

The HR estimate after running for 200 epochs with $f_c = 2f_N$ is shown in Fig. 4.11. Compared to the result in Fig. 4.8, where $f_c = f_N$, the HR estimate computed using aliased LR frames is visually better than the Nyquist-limited case.

Figure 4.11: HR estimate after running POCS with $f_c = 2f_N$ for 200 epochs

The HR estimates for varying levels of aliasing are shown in Fig. 4.12, and the corresponding ISNR curves are shown in Fig. 4.13. The cutoff frequency f_c was chosen using $f_c = kf_N$, where k is a factor that indicates the amount of aliasing present. Aliasing occurs when $k > 1.0$, and the image is Nyquist-sampled when $k = 1.0$. For the simulations, the standard deviation of the Gaussian PSF estimate was chosen to match the actual system PSF as closely as possible, with $\sigma = 3.5/k$. Figures 4.12 and 4.13 show several things. First, aliasing in a satellite sensor is not always undesirable. A sensor system is often designed to have the largest diameter

Figure 4.12: The HR estimates for various amounts of aliasing, with cutoff frequency $f_c = kf_N$, after 200 epochs. Each image has a final ISNR that is shown on its corresponding curve in Fig. 4.13.

Figure 4.13: The effect of aliasing on the resolution enhancement of the test pattern, with cutoff frequency $f_c = kf_N$. Aliasing is present for $k > 1.0$. Every tenth epoch is plotted for clarity.

of telescope that is affordable or will fit on the launch vehicle. The blur that occurs when reducing the size of the detectors to ensure Nyquist-bandlimited data for a given telescope size can be large, and difficult to remove using image restoration techniques. Inverting large blur functions results in undesirable ringing. Second, the results with aliasing are much better than those without aliasing. Each aliased, shifted LR frame contains information not present in the other frames; there is a lower correlation between frames that are highly aliased. For $1.2 < k < 1.8$, aliasing gives us LR images with different shifts in the edge locations, and good restoration of the plus sign edges. For $k > 2.0$, the shifts between frames allow very good qualitative enhancement of both the plus sign and the point sources.

The results of this section have shown the effect of aliasing on the resolution enhancement performance of LR frames simulated using only translation and down-sampling. However, a simple test image was used rather than MTI data. The test image is particularly challenging to the POCS algorithm's convergence due to its maximal contrast (0.0 to 255.0, which is the same range enforced in this simulation by the POCS algorithm using a bounds constraint) and small image features. Satellite imagery does not typically contain such large contrast changes; the pixels in "real world" images are statistically highly correlated with their neighbors [59]. Therefore, to study POCS convergence with a more realistic example, the aliasing of multi-angle satellite images will be examined further in Sect. 4.8.

4.4 Combining Two-look Imagery

The performance of the POCS algorithm with simulated two-look imagery is examined in this section. Using the multi-angle image simulation tools developed in the previous chapter, test data consisting of a nadir image and one off-nadir image are formed. One dataset is generated from the standard “Cameraman” image, shown in Fig. 4.14. This image is often used in image processing literature when testing an algorithm’s performance, since there are strong contrasts, as well as a human face, which allows a qualitative measure of image improvement. The other test input used is an image acquired by the MTI instrument over Albuquerque, NM, over the Isotopes Park baseball field. The image is a 128×128 crop from band A (the visible “blue” band), and is shown in Fig. 4.15. This image allows a quantitative measure of the image improvement possible for remotely-sensed imagery at visible wavelengths, specifically for the MTI sensor.

The POCS algorithm is applied to two images, one at nadir and one at an off-nadir angle θ , to observe the effect of the off-nadir view angle on convergence. The basic parameters of the MTI instrument are used to model the off-nadir image geometry. The height of the sensor is assumed to be 575 km, and the field-of-view (FOV) is approximately that of the MTI instrument. Unlike the MTI, the sensor is modeled by a circular aperture in front of a 64×64 pixel 2D CCD array. The HR grid is defined to be 128×128 pixels, meaning that the output resolution will

Figure 4.14: The original “Cameraman” image, cropped to 128×128 pixels.

Figure 4.15: The original “Isotopes” MTI image, sized 128×128 pixels.

be twice that of the input images in both the x and y directions (four times the number of pixels). However, this sampling grid is finer than the “true” resolution expected, since two images with optimum shifts and no angular movement allows a theoretical resolution increase of only 1.4 from simple geometry. The modeled input LR frames for the “Cameraman” image are shown in Fig. 4.16 and Fig. 4.17. The HR estimates found by applying POCS resolution enhancement are shown in Figs. 4.18 and 4.19 with the corresponding ISNR curves (compared to bilinearly interpolating the nadir image) shown in Fig. 4.20. Observing the HR estimates of the “Cameraman” image, small details in facial features are enhanced. Since each LR frame contained different details, the HR estimates vary on how well they bring out features of interest. Nonetheless, combining only two images results in improvement over the LR nadir image in Fig. 4.16. Repeating the above experiment with the “Isotopes” image, the modeled input LR frames are shown in Fig. 4.21 and Fig. 4.22. The HR estimates are shown in Figs. 4.23 and 4.24 with the ISNR curves shown in Fig. 4.25. Details such as the divided road lanes and parking lot rows are more apparent in the restored HR estimates, with details again varying depending on which off-nadir angle was used. The ISNR values for the “Isotopes” image are approximately 1 dB higher than those for the “Cameraman” image, with the best two-angle combination at $\theta = 0^\circ, 10^\circ$ and an ISNR of 5.4 dB.

Figure 4.16: The nadir LR input “Cameraman” frame, sized 64×64 pixels, enlarged to show detail.

Figure 4.17: The simulated multi-angle LR “Cameraman” frames used as input to the POCS algorithm, 64×64 pixels, at $\theta = 0^\circ, 5^\circ, \dots, 40^\circ$.

Figure 4.18: The HR estimate of the “Cameraman” image using two frames, one nadir and one off-nadir at look angles $\theta = 5^\circ, 10^\circ, 15^\circ, 20^\circ$.

Figure 4.19: The HR estimate of the “Cameraman” image using two frames, one nadir and one off-nadir at look angles $\theta = 25^\circ, 30^\circ, 35^\circ, 40^\circ$.

Figure 4.20: Improvement in SNR for the “Cameraman” image using two frames, one nadir and one off-nadir at various look angles θ .

Figure 4.21: The nadir LR input “Isotopes” frame, sized 64×64 pixels, enlarged to show detail.

Figure 4.22: The simulated multi-angle LR “Isotopes” frames used as input to the POCS algorithm, 64×64 pixels, at $\theta = 0^\circ, 5^\circ, \dots, 40^\circ$.

Figure 4.23: The HR estimate of the “Isotopes” image using two frames, one nadir and one off-nadir at look angles $\theta = 5^\circ, 10^\circ, 15^\circ, 20^\circ$.

Figure 4.24: The HR estimate of the “Isotopes” image using two frames, one nadir and one off-nadir at look angles $\theta = 25^\circ, 30^\circ, 35^\circ, 40^\circ$.

Figure 4.25: Improvement in SNR for the “Isotopes” image using two frames, one nadir and one off-nadir at various look angles θ .

4.5 The Off-nadir Sampling Grid Problem

The placement of an impulse or test pattern within a LR grid affects the algorithm's convergence because the sample spacing goes into and out of phase for the LR frames at different angles, due to the sample spacing increasing by a non-integer amount as the off-nadir angle increases. Some regions will converge well, while others not as well. When the samples are coincident, the resolution enhancement algorithm has a difficult time converging. For off-nadir images, some samples will be well-spaced, while others will not. This leads to a linear shift varying (LSV) sample grid. As an example, consider Fig. 4.26. Sample positions are shown for a “nadir” image of 67×67 pixels, a 10° “off-nadir” image of 65×65 pixels, and a 14° “off-nadir” image of 63×63 pixels. Note that this example does not include perspective skew, but only the relative pixel sizes. The effective spacing of the sample points is unevenly distributed, resulting in areas with poor coverage. The POCS algorithm (or any other multi-frame resolution enhancement algorithm) will have difficulties improving the resolution in these regions. The non-integer ratios of the nadir and off-nadir sampling grids are problematic since it is nearly impossible to ensure the optimal spacing of sample points when acquiring multiple-look images. To form a resolution-enhanced image, one must hope that the sampled observations in a region of interest are sufficiently shifted between looks to provide the additional information required. However, the POCS algorithm can partially compensate for

insufficient samples because additional constraint sets may be applied to improve the algorithm convergence. In Ref. [46], it was shown that an amplitude constraint improved the convergence rate of the POCS method when the number of samples of a one-dimensional function was insufficient to allow reconstruction.

To quantitatively show how the convergence of POCS varies with the distribution of sample points, the algorithm is applied to a two-look “Cameraman” dataset. Figure 4.27 shows the locations of sampling points for a nadir frame at $\theta = 0^\circ$ and an off-nadir frame at $\theta = 7^\circ$. The black box surrounds an area with sub-optimal sample spacing, with a distance between the corresponding sample points in each frame less than a tenth of a pixel. After twenty epochs of running the POCS algorithm, the ISNR over the entire image is 3.00 dB. In the region with “bad” sample spacing, the ISNR is 2.47 dB, while in the surrounding region with “good” sample spacing the ISNR is 3.26 dB.

Figure 4.26: Grids of different sizes overlaid. Blue points represent the pixel positions for a “nadir” image of 67×67 pixels, green points represent a 10° “off-nadir” image of 65×65 pixels, and red points represent a 14° “off-nadir” image of 63×63 pixels. Non-integer sampling ratios result in areas with good sampling coverage (areas where blue, green, and red dots are equally spaced) and bad sampling coverage (the region in the center).

Figure 4.27: Distribution of sampling positions for two frames, one nadir and one off-nadir at a look angle of 7° . The region inside the box has poor sample spacing compared to the region outside the box, resulting in different ISNR's in each restored region after 20 iterations of POCS (the ISNR is 2.47 dB inside the box and 3.26 dB outside the box).

4.6 Combining Multi-look Imagery

In this section, the performance of the POCS algorithm with simulated multi-look imagery is examined. Ten images, one nadir and nine off-nadir, are combined to form a HR image. The parameters used to model the off-nadir image geometry are the same as those for the MTI instrument.

For the first multi-look experiment, varying numbers of images with a $\Delta\theta = 8^\circ$ separation are combined. Figures 4.28 and 4.30 show the HR estimates from the $\theta = 0^\circ, 8^\circ, \dots, 40^\circ$ case for the “Cameraman” and the “Isotopes” image, respectively. Figures 4.29 and 4.31 show the corresponding ISNR curves. For the “Isotopes” test image, the highest ISNR occurs at 40° , using six LR frames, but the final ISNR of approximately 8.2 dB may be achieved using only four or five images. The 40° image provides little additional information. For the “Cameraman” image, the 40° image does help the final result by about 0.5 dB over the $\theta = 32^\circ$ maximum case. The inclusion of the image at 48° makes the results worse; at this angle, the off-nadir GSD is more than twice that of the nadir GSD. Therefore, off-nadir images at $\theta > 48^\circ$ do not help improve the resolution. Since the MTI acquires its second look near 50° or 55° , it is therefore unlikely that standard two-look MTI data could be used successfully for resolution enhancement.

Ten images with 5° separation are generated next, with a maximum angle of 45° (designed to be less than 48° since the images fail to provide helpful information

Figure 4.28: HR estimate for six frames of the “Cameraman” image, $\theta = 0^\circ, 8^\circ, 16^\circ, 24^\circ, 32^\circ, 40^\circ$.

Figure 4.29: The ISNR for 2 to 10 frames of the “Cameraman” image, $\theta = 0^\circ, 8^\circ, 16^\circ, \dots, 72^\circ$.

Figure 4.30: The HR estimate for six frames of the “Isotopes” MTI image, $\theta = 0^\circ, 8^\circ, 16^\circ, 24^\circ, 32^\circ, 40^\circ$.

Figure 4.31: The ISNR for 2 to 10 frames of the "Isotopes" MTI image, $\theta = 0^\circ, 8^\circ, 16^\circ, \dots, 72^\circ$.

past that point). Figures 4.32 and 4.34 show the six-frame HR estimates for the two images using $\theta = 0^\circ, 5^\circ, 10^\circ, 15^\circ, 20^\circ, 25^\circ$; Figs. 4.33 and 4.35 show the corresponding ISNR curves with $\Delta\theta = 5^\circ$ up to a maximum off-nadir angle of $\theta = 45^\circ$. In both cases, the maximum ISNR is close to 9 dB. After combining five or six images, the ISNR is not made better by combining more images, but the ISNR values do not get worse, either. Therefore, six LR frames are ideal for this viewing scenario, as long as the images are acquired for $\theta < 48^\circ$ off-nadir so that they do not cause divergence of the POCS algorithm.

Figures 4.36 and 4.38 show the HR estimates using fewer frames by removing some of the intermediate frames from the previous experiment, with Figs. 4.37 and 4.39 giving the ISNR curves using fewer frames. Combining five or six images gives a final ISNR near 8 dB, between 0.5 dB and 1 dB less than the cases with more images. For the “Isotopes” image, an approximately 8.5 dB improvement is achieved using five images with either $\theta = 0^\circ, 5^\circ, 10^\circ, 15^\circ, 20^\circ$ or $\theta = 0^\circ, 5^\circ, 15^\circ, 25^\circ, 35^\circ$. Thus, the algorithm does not require a large (> 10) number of images or images with exact $\Delta\theta$ spacing.

If the maximum angle is set at 40° , and the two to ten LR frames occur at equally-spaced angle intervals, the results are practically the same as before; the HR estimates are shown in Figs. 4.40 and 4.42 and the ISNR curves are shown in Figs. 4.41 and 4.43.

Figure 4.32: The HR estimate for six frames of the “Cameraman” image, $\theta = 0^\circ, 5^\circ, 10^\circ, 15^\circ, 20^\circ, 25^\circ$.

Figure 4.33: The ISNR for 2 to 10 frames of the “Cameraman” image, $\theta = 0^\circ, 5^\circ, 10^\circ, \dots, 45^\circ$.

Figure 4.34: The HR estimate for six frames of the “Isotopes” image, $\theta = 0^\circ, 5^\circ, 10^\circ, 15^\circ, 20^\circ, 25^\circ$.

Figure 4.35: The ISNR for 2 to 10 frames of the “Isotopes” MTI image, $\theta = 0^\circ, 5^\circ, 10^\circ, \dots, 45^\circ$.

Figure 4.36: The HR estimate for five frames of the “Cameraman” image, $\theta = 0^\circ, 5^\circ, 15^\circ, 25^\circ, 35^\circ$.

Figure 4.37: The ISNR for 2 to 6 frames of the “Cameraman” image, $\theta = 0^\circ, 5^\circ, 15^\circ, \dots, 45^\circ$.

Figure 4.38: The HR estimate for five frames of the “Isotopes” image, $\theta = 0^\circ, 5^\circ, 15^\circ, 25^\circ, 35^\circ$.

Figure 4.39: The ISNR for 2 to 6 frames of the “Isotopes” MTI image, $\theta = 0^\circ, 5^\circ, 15^\circ, \dots, 45^\circ$.

Figure 4.40: The HR estimate for seven frames of the “Cameraman” image, $\theta = 0^\circ, 6.7^\circ, 13.3^\circ, 20^\circ, 26.7^\circ, 33.3^\circ, 40^\circ$.

Figure 4.41: The ISNR for 2 to 10 frames of the “Cameraman” MTI image, using equally spaced angles from 0° to 40° .

Figure 4.42: The HR estimate for seven frames of the “Isotopes” image, $\theta = 0^\circ, 6.7^\circ, 13.3^\circ, 20^\circ, 26.7^\circ, 33.3^\circ, 40^\circ$.

Figure 4.43: The ISNR for 2 to 10 frames of the “Isotopes” MTI image, using equally spaced angles from 0° to 40° .

4.7 Combining Symmetric Three-look Imagery

The two-look experiments of Sect. 4.4 assumed that the imaging system operated like the MTI sensor, first acquiring a nadir image and then pointing back to acquire a second image. A logical improvement in the image collection is to begin taking images as soon as the ground target is within view at some forward-pointing off-nadir angle, and then continue to point the satellite and take imagery until the sensor has passed over the ground target and is pointing backward at some maximum off-nadir angle. This approach allows more images at look angles close to nadir to be collected. Since near-nadir imagery has the highest resolution (the IFOV is smallest when the distance from the satellite to the ground is at a minimum), as many images as possible should be taken close to nadir. The number of images that may be taken is limited by the time required to re-point the satellite. At a minimum, three images, one at nadir and two at symmetric off-nadir positions $\pm\theta$, should be used to maximize the quality of the data input to a resolution enhancement algorithm. To explore the idea of using symmetric off-nadir images, the POCS algorithm is applied to simulated three-look imagery. The LR dataset is formed from a nadir image ($\theta = 0$), a forward-pointing off-nadir image at $-\theta$, and a backward-pointing off-nadir image at $+\theta$. The angle θ is varied for each simulation to determine the useful range of off-nadir angles for resolution enhancement. The HR estimates for the “Camera-man” three-look imagery for symmetric off-nadir angles of $\pm\theta$ are shown in Figs. 4.44

and 4.45. The corresponding ISNR curves are shown in Fig. 4.46. Comparing the ISNR results here with the equally-spaced nadir/backward-pointing results shown in Fig. 4.41, the asymmetric case with three looks at $\theta = 0^\circ, 20^\circ, 40^\circ$ has an ISNR of 5 dB. For the symmetric case using the same $\Delta\theta = 20^\circ$, so that $\theta = -20^\circ, 0^\circ, 20^\circ$, the ISNR is 6.2 dB, a 1.2 dB improvement. The asymmetric acquisition geometry requires four images rather than the three needed in the symmetric case to attain the nearly the same ISNR of approximately 7 dB. The three-look HR estimates for the “Isotopes” image are shown in Figs. 4.47 and 4.48, with corresponding ISNR curves shown in Fig. 4.49. The $\Delta\theta = 20^\circ$ case for symmetric viewing gives an ISNR of 6.2 dB, while the asymmetric case gives an ISNR of 6.9 dB, an improvement of 0.7 dB. Symmetric viewing with $\theta = -15^\circ, 0^\circ, 15^\circ$ gives a 7.5 dB improvement compared to the similar 7.7 dB improvement using $\theta = 0^\circ, 13.3^\circ, 26.7^\circ, 40^\circ$; three symmetric frames are needed compared to four asymmetric frames for equivalent improvement of the “Isotopes” image. Therefore, symmetric viewing is better than asymmetric viewing for POCS resolution enhancement.

Figure 4.44: The HR estimate of the “Cameraman” image using three frames, one nadir and one off-nadir at look angles $\theta = \pm 5^\circ, \pm 10^\circ, \pm 15^\circ, \pm 20^\circ$.

Figure 4.45: The HR estimate of the “Cameraman” image using three frames, one nadir and one off-nadir at look angles $\theta = \pm 25^\circ, \pm 30^\circ, \pm 35^\circ, \pm 40^\circ$.

Figure 4.46: Improvement in SNR for the “Cameraman” image using three frames, one nadir and two off-nadir at look angles $\pm\theta$.

Figure 4.47: The HR estimate of the “Isotopes” MTI image using three frames, one nadir and one off-nadir at look angles $\theta = \pm 5^\circ, \pm 10^\circ, \pm 15^\circ, \pm 20^\circ$.

Figure 4.48: The HR estimate of the “Isotopes” MTI image using three frames, one nadir and one off-nadir at look angles $\theta = \pm 25^\circ, \pm 30^\circ, \pm 35^\circ, \pm 40^\circ$.

Figure 4.49: Improvement in SNR for the “Isotopes” MTI image using three frames, one nadir and two off-nadir at look angles $\pm\theta$.

4.8 Aliasing and Three-look Imagery

The topic of aliasing is now revisited using three-look simulated imagery. Two issues to explore are the selection of the elliptical Gaussian PSF width, σ , and how aliasing affects the resolution enhancement of multi-angle images. Recall that aliasing is present in the LR frames with an optical cutoff frequency of $f_c = kf_N$ when the Nyquist factor $k > 1.0$. Aliased and non-aliased data sets, for $0.8 < k < 2.0$, are created at symmetric look angles $\theta = -20^\circ, 0^\circ, +20^\circ$. The POCS algorithm is then applied to the three-look imagery using an estimated elliptical Gaussian system PSF with varying widths σ .

The aliased three-look 64×64 pixel “Cameraman” and “Isotopes” data sets with $k = 2.0$ are shown in Figs. 4.50 and 4.52, along with their original 128×128 pixel images. Figures 4.51 and 4.53 show the nadir LR frames bilinearly interpolated to the HR grid at twice the size of the LR frames. The POCS algorithm is initialized with the interpolated image. Note that the road medians seen in the original 128×128 “Isotopes” image (upper left of Fig. 4.52) are not visible in the interpolated image.

Figures 4.54 to 4.67 show the “Cameraman” HR estimates using a value for σ that gives the best ISNR, along with their corresponding ISNR curves. Likewise, Figs. 4.56 to 4.69 show the “Isotopes” HR estimates using a value for σ that gives the best ISNR, along with their corresponding ISNR curves.

Figure 4.50: The original “Cameraman” image (upper left) and the aliased three-look images for $k = 2.0$ (upper right at -20° , lower left at 0° , and lower right at $+20^\circ$).

Figure 4.51: The 64×64 nadir LR “Cameraman” frame for $k = 2.0$ after bilinear interpolation to a 128×128 pixel grid.

Figure 4.52: The original “Isotopes” MTI image (upper left) and the aliased three-look images for $k = 2.0$ (upper right at -20° , lower left at 0° , and lower right at $+20^\circ$).

Figure 4.53: The 64×64 nadir LR “Isotopes” frame for $k = 2.0$ after bilinear interpolation to a 128×128 pixel grid.

The aliased image cases are studied first, using $k = 2.0$ and $k = 1.4$. Figures 4.54 and 4.58 show the “Cameraman” HR estimates at twice the resolution of the LR frames. When $k = 2.0$, the best INSR is 6.49 dB, and occurs when the elliptical Gaussian PSF has width $\sigma = 1.8/k = 1.8/2.0 = 0.9$, as shown in Fig. 4.55. Similarly, from Fig. 4.59, it is observed that when $k = 1.4$, the best INSR is 4.35 dB, and occurs when the estimated PSF has width $\sigma = 1.8/k = 1.8/1.4 = 1.29$. Figures 4.56 and 4.60 show the “Isotopes” HR estimates at twice the resolution of the LR frames. When $k = 2.0$, the best INSR is 7.73 dB, also using an elliptical Gaussian PSF width of $\sigma = 0.9$, shown in Fig. 4.57. In Fig. 4.61, when $k = 1.4$, the best INSR is 6.16 dB, also using an estimated PSF width of $\sigma = 1.29$. As was observed with the aliased, translated test images in Sect. 4.3, an increase in aliasing, or the Nyquist factor k , results in better HR estimates. The best estimate for the “Cameraman” image has an ISNR that is more than 2 dB better for $k = 2.0$ compared to $k = 1.4$. For the “Isotopes” MTI image, the best HR estimate has an ISNR that is nearly 1.6 dB better for $k = 2.0$ compared to $k = 1.4$. The ISNR plots for $k = 2.0$ and $k = 1.4$ also show that using an estimated PSF that is too wide ($\sigma > 0.9$ for $k = 2.0$ and $\sigma > 1.29$ for $k = 1.4$) results in unwanted ringing artifacts and POCS algorithm divergence. If σ is too small, POCS does not give optimal improvement because not enough deblurring occurs. Therefore, correctly estimating the system PSF is critical for obtaining optimal resolution enhancement. The estimated PSF width must account for the combined PSF of the optics and the detector. For a

multispectral system such as the MTI, this means that the POCS algorithm must use estimated system PSF's of different widths for each band.

Figure 4.54: The HR “Cameraman” image for 3 frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, $k = 2.0$, $\sigma = 0.9$.

Figure 4.55: The ISNR of the enhanced “Cameraman” image for varying widths σ of the estimated PSF, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $f_c = 2f_N$.

Figure 4.56: The HR “Isotopes” image for 3 frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, $k = 2.0$, and $\sigma = 0.9$.

Figure 4.57: The ISNR of the enhanced “Isotopes” image for varying widths σ of the estimated PSF, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $f_c = 2f_N$.

Figure 4.58: The HR “Cameraman” image for 3 frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, $k = 1.4$, and $\sigma = 1.29$.

Figure 4.59: The ISNR of the enhanced "Cameraman" image for varying widths σ of the estimated PSF, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $f_c = 1.4f_N$.

Figure 4.60: The HR “Isotopes” image for 3 frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, $k = 1.4$, and $\sigma = 1.29$.

Figure 4.61: The ISNR of the enhanced “Isotopes” image for varying widths σ of the estimated PSF, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $f_c = 1.4f_N$.

Next the Nyquist-sampled and non-aliased data sets are considered, using $k = 1.0$ and $k = 0.8$. The “Cameraman” HR estimate and the ISNR curves for $k = 1.0$ are shown in Figs. 4.62 and 4.63, respectively. Similarly, the “Isotopes” HR estimate and the ISNR curves for $k = 1.0$ are shown in Figs. 4.64 and 4.65. The HR images contain undesirable ringing artifacts. Nyquist-sampled imagery is difficult to improve qualitatively even though the ISNR indicates resolution improvement. The ISNR is 2.50 dB for the “Cameraman” image and is 4.55 dB for the “Isotopes” image when $k = 1$. However, several details are not resolved compared to the original images. The roads in the “Isotopes” image do not show two lanes with a median, and the parking lot above Isotopes Park no longer shows rows of cars. Facial features are not improved in the “Cameraman” image. Figures 4.66 and 4.67 show the HR “Cameraman” estimate and the ISNR curves for $k = 0.8$. The optimal PSF for the “Cameraman” image has a width of $\sigma = 1.5/k = 1.5/0.8 = 1.88$. Figures 4.68 and 4.69 show the HR estimate and the ISNR curves for the “Isotopes” image using $k = 0.8$. For this non-aliased case, the optimal PSF for the “Isotopes” image has a width of $\sigma = 1.8/k = 1.8/0.8 = 2.25$. As was the case for Nyquist-sampled imagery, ringing prevents a visually good HR estimate even when the optimal estimated system PSF is used in the POCS algorithm. It may be concluded that little qualitative improvement may be expected by applying the POCS resolution enhancement algorithm to images that are not aliased, despite

efforts to obtain imagery at symmetric off-nadir angles and to use the best estimated system PSF width, σ , using the elliptical Gaussian PSF.

To summarize the results of this section, Figs. 4.70 and 4.71 show the ISNR curves for the “Cameraman” and the “Isotopes” images for differing Nyquist factors k , using a PSF width of $\sigma = 1.8/k$.

Figure 4.62: The HR “Cameraman” image for 3 frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, $k = 1.0$, and $\sigma = 1.8$.

Figure 4.63: The ISNR of the enhanced “Cameraman” image for varying widths σ of the estimated PSF, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $f_c = f_N$.

Figure 4.64: The HR “Isotopes” image for 3 frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, $k = 1.0$, and $\sigma = 1.8$.

Figure 4.65: The ISNR of the enhanced “Isotopes” image for varying widths σ of the estimated PSF, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $f_c = f_N$.

Figure 4.66: The HR “Cameraman” image for 3 frames, $k = 0.8$, and $\sigma = 2.25$.

Figure 4.67: The ISNR of the enhanced “Cameraman” image for varying widths σ of the estimated PSF, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $f_c = 0.8f_N$.

Figure 4.68: The HR “Isotopes” image for 3 frames, $k = 0.8$, and $\sigma = 2.25$.

Figure 4.69: The ISNR of the enhanced "Isotopes" image for varying widths σ of the estimated PSF, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $f_c = 0.8f_N$.

Figure 4.70: The ISNR of the enhanced “Cameraman” image for varying Nyquist factors k , where $f_c = kf_N$, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $\sigma = 1.8/k$.

Figure 4.71: The ISNR of the enhanced “Isotopes” image for varying Nyquist factors k , where $f_c = kf_N$, using three frames at $\theta = -20^\circ, 0^\circ, 20^\circ$, and $\sigma = 1.8/k$.

4.9 Resolution Enhancement of Multispectral Imagery

Resolution enhancement for an instrument like the MTI has an additional component not yet addressed: multiple spectral bands. It is possible to perform *multispectral* spatial-resolution enhancement. During each “look,” the MTI instrument collects many images with the same view angle, one for each spectral band. Multiple frames, each at the same wavelength but at different angles, may be combined using the standard POCS algorithm already discussed. Repeating this process for each band, a multispectral HR estimate may be formed by stacking the HR estimates for the individual bands. The concept is shown in Fig. 4.72.

In this section, real data from a multispectral fluorescence confocal imaging system are used to show how POCS may be used to form high resolution images using multiple spectral bands. The imaging system, developed in the Spectroscopy, Imaging, and Molecular Chemistry Group at Los Alamos National Laboratory (LANL), uses multiple lasers to scan across a living sample that has been stained with a fluorescent dye, or fluorophore. The fluorescence emission signals at incremental spatial positions and at each wavelength are spectrally filtered, detected by a photomultiplier tube (PMT), and stored as digital image. The use of more than one laser allows multiple types of cellular structures to be imaged simultaneously. Two lasers are used in this imaging system: an Argon laser at 488 nm and a He-Ne laser at 453 nm. The fluorophores excited by the laser illumination give emissions at longer

Figure 4.72: Formation of a multispectral high-resolution image

wavelengths than that of the laser. The filters record emissions in a “green” channel from 500 to 530 nm and a “red” channel for emissions above 550 nm. Figure 4.73 shows an image of a cell acquired by the imaging system. The green channel allows imaging of actin fibers and the red channel allows imaging of mitochondria.

To collect data for input to the POCS algorithm, nine LR frames were acquired by the microscope by translating the cell sample with respect to the optics in the x and the y directions in increments of 100 nm using a precision stepper motor. Each LR image has a 75 nm pixel size. The 100 nm step size was the smallest step size the stepper motor could take. The lasers cause photobleaching of the sample to occur, meaning that successive frames have reduced contrast with respect to the previous frame. Therefore, the LR frames must be contrast-matched prior to forming the HR estimate using POCS. One of the nine LR frames is shown in Fig. 4.73, and is 400×400 pixels in size. The HR estimate is computed on a grid that is three times larger, at 1200×1200 pixels, or 25 nm on a side for each pixel. The estimated HR image at $3\times$ the original resolution is shown in Fig. 4.74. Compared to the LR image, details of the cell’s structure are qualitatively better in the estimated HR image (according to the author as well as the microscope’s designers at LANL). The green actin fibers appear more continuous rather than “speckled,” and the shape and contrast of the mitochondria is improved. A second example is shown in Figs. 4.75 and 4.76. Note the detail of the thin actin fibers, especially the thin fiber connecting the two cells, and the enhanced visibility of the red mitochondria.

Figure 4.73: One LR frame (out of nine) of a two-spectral-band cell image

Figure 4.74: The HR estimate of the multispectral cell image with $3\times$ resolution increase

Figure 4.75: One LR frame of a two-spectral-band cell image.

Figure 4.76: HR estimate of multispectral cells

Although a visual comparison of the cell images shows a qualitative improvement, a quantitative measure of improvement is difficult since the ISNR cannot be computed without knowledge of the “original” object. As an alternative way to quantitatively assess the POCS algorithm performance, images were acquired of standard-sized 100 nm latex fluorescence beads, or microspheres, to see if their resolution could be enhanced. Microspheres are commonly used to adjust the depth focus of scanning microscopes. The acquired imagery was very large, containing hundreds of identical microspheres, so a small region of the image was cropped to form a representative test image containing only a few beads. The before and after images are shown in Figs. 4.77 and 4.78. The LR frames make the beads appear to be 450 nm across. After applying POCS, the beads are not resolved to 100 nm, but appear about 300 nm in diameter. The results are highly sensitive to the different contrast between the frames, the registration, as well as the width of the estimated PSF. The stepper motor has a precision of $\pm 5\text{nm}$, meaning the registration error between any two frames could be up to 10 nm in both the x and the y directions, or nearly one-half pixel on the HR grid. To achieve improved resolution enhancement results from this microscope data, registration estimation methods could be used rather than assume perfect stepper motor translation as was done in this case. Also, using microspheres that have a thin layer of dye rather than dye throughout would ensure that the depth focus is correct; the microspheres in the acquired images appear to be different sizes, indicating that the bead cross-sections are not necessarily

through the center of each bead. In addition, the imagery was acquired at the highest resolution possible for the microscope to test whether POCS could reconstruct the beads at a resolution better than that of the microscope. Since these images are nearly diffraction-limited, not much improvement beyond the 300 nm optical resolution can be expected. However, POCS could still be useful for scanning microscope imagery; by reducing the exposure time and acquiring multiple images, less photobleaching of the sample occurs. Nonetheless, the microscope examples demonstrate the ability of POCS to improve real multispectral data under non-ideal conditions.

Figure 4.77: One LR frame of fluorescence beads

Figure 4.78: HR estimate of the fluorescence beads

CHAPTER 5

PRE-PROCESSING ISSUES

5.1 Overview

Several pre-processing steps can improve the results of resolution enhancement algorithms when applied to multi-angle, remotely-sensed images. This chapter discusses remote sensing issues that do not always arise when applying resolution enhancement algorithms to standard images in the field of image processing. These issues include sensor calibration, atmospheric correction, and reflectance properties of materials. Sensor calibration ensures that the pixel values in an image are accurate measurements of the objects or materials in a scene. Also, satellite-based sensors acquire images through the earth's atmosphere, and the effects of the atmosphere ideally should be removed from the multi-angle images before fusing them because the path length from the sensor to the surface of the earth becomes larger with increasing angles with respect to nadir, and the sun's position is different from one image to another. For small angles and short times between subsequent images, atmospheric effects may not change dramatically and could be neglected. However, removing the atmospheric effects allows a retrieval of ground reflectance, which is

needed for another pre-processing step: bidirectional reflectance distribution function correction. Each of these pre-processing steps is discussed in detail in the following sections.

5.2 Sensor Calibration

Most sensor systems store their data digitally, typically as an integer value, with a precision given by the number of bits per pixel [21]. The stored data value for a pixel is commonly referred to as the digital count (DC) or the digital number (DN). Sensor calibration is required to convert the digital numbers at the focal plane of an instrument into physical units, such as at-sensor radiance. Without calibration, there could be differences from pixel to pixel due to variations in detector fabrication, or even condensation on the system optics, for instance. This would lead to sub-optimal results when applying a resolution enhancement algorithm. Sensors are characterized and calibrated before flight, but once launched, the performance of the system changes. Therefore, calibration is usually done periodically throughout the lifetime of a sensor. Some sensors, such as the MTI, are designed with an onboard calibration system to allow frequent and precise data calibration. When no onboard calibration system exists, as is the case for many sensors, calibration may be done by using deep-space looks or, alternatively, by collecting concurrent “ground truth” measurements. In this dissertation, the images are assumed to be correctly calibrated. However, all remote sensing imagery has some degree of uncertainty

in its calibration, and poorly calibrated images cannot be combined to form high-resolution imagery. Therefore, sensor calibration is important to consider when doing resolution enhancement using multiple low-resolution images.

5.3 Atmospheric Correction

One must also consider the effects of the atmosphere when taking measurements of the ground from a space-based or high altitude airborne sensor [21]. Radiation leaving the ground may be absorbed or scattered by the atmosphere, resulting in attenuation of the desired signal. Additionally, direct scattering of solar radiation by the atmosphere increases the radiance at the sensor, and these effects are different in each spectral band. These two effects make it a challenge to determine the true radiance or reflectance of an object at the Earth's surface. In remote sensing, compensating for the effects of the atmosphere is called *atmospheric correction*. The primary inputs to atmospheric correction are the path length from the ground target to the sensor and the angle between the sun and the sensor. The desired output of an atmospheric correction algorithm is the ground reflectance, ρ_g , at each pixel. Ground reflectance is a more useful measurement than the at-sensor radiance because it is a material-specific property. Reflectance properties of materials are discussed in more detail in Sect. 5.4.

For visible and near infrared wavelengths (the solar regime), radiance reaching the sensor follows three primary paths from the sun [21]. These paths are shown

in Fig. 5.1. *Upwelled radiance* from the atmosphere is the component removed during atmospheric correction. These photons are scattered by the atmosphere before reaching the ground, and reduce the contrast of objects on the ground as viewed by the sensor. *Direct radiance* may be partially or entirely absorbed by the atmosphere before reaching the sensor. The direct radiance photons illuminate objects on the ground. A human observer would perceive this illumination as a sunlit area. The photons that comprise *skylight* are scattered by the atmosphere and then illuminate objects on the ground. Objects that are not directly illuminated by the sun (that is, they are in the shadow of another object) are still visible due to skylight illumination.

Figure 5.1: Main paths of solar energy to a sensor

Applying atmospheric correction prior to running a resolution enhancement algorithm is desirable for any image analysis task that requires high radiometric precision. A procedure for atmospheric correction is as follows. Each satellite image that is input to the resolution enhancement algorithm will have a sun and view angle associated with it. Given these sun and view angles (zenith and azimuth), a radiative transfer code may be run with these sun and view angles for multiple surface reflectances, assuming a fixed aerosol case. The output from the radiative transfer code will contain a relative radiance output for the rough center wavelength of each sensor spectral band for a set of assumed surface reflectances. The relative radiances are converted to absolute radiances by multiplying them by the incident solar irradiance, E_0 , at the top of the atmosphere. The value for E_0 must be band-averaged, incident normal to the atmosphere, and corrected for sun-earth distance. This set of reflectance to absolute radiance values may then be used as a lookup table. To correct a pixel in a scene, given the at-sensor radiance at that pixel, L_{sensor} , and the wavelength λ , or band, of that image, the nearest two predicted radiances from the radiative transfer code runs are located in the proper lookup table for that band and the values are linearly interpolated to determine the ground reflectance, ρ_g , corresponding to that sensor radiance. For resolution enhancement preprocessing, it is reasonable to assume that the same lookup table may be used for all of the pixels within a single image, as long as the imagery does not contain

haze or partial cloud cover, since the wavelength, path length, sun angle, and view angle are essentially the same over an image.

5.4 Bidirectional Reflectance Distribution Function (BRDF) Correction

The BRDF of a surface describes the reflectance of a surface as a function of view angle for a given illumination source at a fixed angle. It is an intrinsic property of materials that should be taken into consideration when analyzing remotely-sensed images. The BRDF, f_r , in units of $[\text{sr}^{-1}]$, is defined as

$$f_r(\theta_i, \phi_i; \theta_r, \phi_r; E_i) = \frac{dL_r(\theta_i, \phi_i; \theta_r, \phi_r; E_i)}{dE_i(\theta_i, \phi_i)} \quad (5.1)$$

where θ_i and ϕ_i are the elevation and azimuth angles of the incident light, E_i $[\frac{W}{m^2}]$ is the irradiance of the incident light, and θ_r and ϕ_r are the elevation and azimuth angles of the reflected radiance L_r $[\frac{W}{m^2 sr}]$ [60]. In practice, the BRDF as defined above cannot be measured directly because all detector systems have a nonzero field-of-view (FOV), meaning that a measurement must be made over a cone defined by a small range of angles θ_r, ϕ_r . Therefore, the BRDF is assumed to vary slowly over the FOV and measurements are made using instruments with a small FOV.

The main steps for BRDF correction of an image are shown in Fig. 5.2. To do BRDF correction, the spectral profile at each pixel is needed to determine the identity of the material, such as soil, vegetation, water, concrete, etc. Then, standard tables of the BRDF response for a given material as a function of viewing and

Figure 5.2: Flow diagram of BRDF correction

illumination angle may be used to adjust the pixel values to look as if the identified material had been viewed by the imaging system from nadir. To identify the materials present, the pixels in the image must be assigned to different classes using an *image classification* algorithm. Image classification algorithms identify the pixel locations of various materials in an input image and assign a “class” or label to each material. Classification algorithms come in two varieties: supervised and unsupervised. In supervised classification, the classifier is trained with a labeled dataset and the error, or cost, is minimized for the training data. Then, the trained classifier may be used to label similar data outside of the training set. Unsupervised learning does not use labeled training data, but tries to group the input data into several clusters. The number of desired clusters is often the only input to this type of classifier. Unsupervised classification gives the location and the number of different materials in a scene, but does not normally perform the more difficult task of identifying the materials. Standard classification methods include k-means,

minimum-distance-to-means, parallelepiped, maximum likelihood, and spectral angle mapping (SAM) [16, 61]. Sophisticated supervised classification methods like GENIE [62–64], an image classification system based on genetic algorithms, are becoming increasingly popular.

Standard BRDF responses for various materials are generated by measuring real materials in the field using specialized instrumentation. As an example, the Remote Sensing Group (RSG) of the Optical Science Center at The University of Arizona has developed an imaging radiometer to take field measurements of the relative angular reflectance of a material [65]. The system uses a four-band 2D CCD array and a fisheye lens. This arrangement allows retrieval of surface BRDF without having to rotate the system to collect data at a wide range of angles. Data sets of phase value versus scattering angle are collected. The scattering angle, $\Theta(x, y)$, is computed for each pixel location (x, y) in the BRDF camera image as

$$\Theta(x, y) = \arccos [\cos \theta_i \cos \theta_v + \sin \theta_i \sin \theta_v \cos (\phi_v - \phi_i)] \quad (5.2)$$

where θ_i is the incident solar zenith angle, θ_v is the viewed zenith angle with respect to the camera at pixel location (x, y) , ϕ_v is the viewed azimuth angle with respect to the camera at pixel location (x, y) , and ϕ_i is the angle of the solar principal plane [65, 66]. The BRDF camera collects nadir-normalized radiance values sampled at one degree phase angle increments [65]. Data are next fit to a modified Pinty-Verstraete equation to generate a table of phase value versus scatter angle,

$$P(\Theta) = a + b \cos \Theta + c \frac{3 \cos^2 \Theta - 1}{2} \quad (5.3)$$

where P is the scattering phase function, Θ is the scattering angle, and a , b , and c are the coefficients found by applying a least-squares fit to the data [67]. These tables of phase value $P(\Theta)$ versus scatter angle Θ may then be used to do BRDF correction of the images for a given date. Points are found on the phase value curve at the nadir and off-nadir scatter angles Θ_n and Θ_o of the input low-resolution frames. Then, the ratio of the corresponding phase values, P_n and P_o , is used to adjust the reflectance in a given pixel to appear like a nadir reflectance:

$$\rho_{new} = \rho_{old} * \frac{P_n}{P_o}. \quad (5.4)$$

The BRDF curves must be known for each identified material in the scene. If materials are not known, as is often the case, then any BRDF correction is problematic to implement. One can make an educated guess based on a visual identification of features; a city road or parking lot is likely to be made of asphalt. However, if resolution enhancement is the task at hand, a user is unlikely to know the identity of the material(s) in a region of interest because there is not high enough resolution in a single image. If, after applying a resolution enhancement algorithm, a user can see the shape of the feature of interest, an educated guess may be made about the material type. This new knowledge would then allow a refinement to the image based on a BRDF correction.

5.5 Experiment: Atmospheric and BRDF Effects

In this section, the “Isotopes” MTI image is used to generate multi-angle datasets with BRDF or atmospheric effects. The upwelled radiance, also called the path radiance, is modeled to determine how it affects the resolution enhancement of multi-angle imagery. In a separate simulation, the grass lawn of the baseball field in the “Isotopes” image is altered to simulate the effect of BRDF with changing view angle.

As discussed previously, a radiative transfer code is normally used to model the path radiance. However, with some reasonable assumptions, a very simple model of atmospheric path radiance may be formed. Assuming a sensor view angle of no greater than 60° and a thin atmosphere, the optical depth as a function of the angle may be considered to be directly proportional to the increase in path length ([68], p. 105):

$$\delta(\theta) \propto \sec \theta. \quad (5.5)$$

An estimate of the path radiance at nadir, $L_p(0)$, may be found by measuring the pixel value in an area of dark vegetation, such as the baseball field in the “Isotopes” image. An off-nadir image at view angle θ with atmospheric path radiance effects is then simulated by adding a constant off-nadir path radiance value, $L_p(\theta)$, to all pixels in the original image prior to applying the projective transform and downsampling steps:

$$L_p(\theta) = L_p(0) * (\sec \theta - 1.0). \quad (5.6)$$

The “Isotopes” image with modeled path radiance is shown in Fig. 5.3, using look angles of $\theta = -50^\circ, 0^\circ, +50^\circ$. The off-nadir images are brighter due to the increased upwelled radiance at the longer off-nadir path length. If the POCS algorithm is applied to the uncorrected data set, the algorithm diverges, as shown in Fig. 5.4, resulting in an unacceptable “speckled” HR estimate. Uncorrected three-look data sets are formed for various off-nadir angles to determine at what angle the POCS algorithm diverges if given data that has not had atmospheric correction applied. The resulting ISNR curves are shown in Fig. 5.5. Compared to the ISNR values for three-look imagery without modeling path radiance, shown in Fig. 4.49, the ISNR values are approximately 1.1 dB lower. Imagery at $\theta > 40^\circ$ begins to pose a problem for POCS. After a few iterations, the inconsistent LR data causes ringing in the HR estimate. It may be concluded that atmospheric correction is needed when the LR frames are acquired at $\theta > 40^\circ$ to ensure convergence of the algorithm. However, assuming the off-nadir path radiance is constant over the image, it is easy to pre-correct the imagery by subtracting the bias due to atmospheric path radiance even if the off-nadir angles are not known. Alternatively, the contrast of the LR frames could be matched using histogram equalization. The HR estimate with the atmospheric term subtracted for the $\theta = -50^\circ, 0^\circ, +50^\circ$ three-look imagery is shown in Fig. 5.6. The final ISNR is 2.79 dB with the correction. For comparison, without correcting the atmospheric path radiance, the ISNR is 2.07 dB. Thus, the bias subtraction improves the HR estimate by 0.72 dB. The simple bias removal is

therefore an effective method to ensure that the LR frames are “consistent,” as long as one can assume that the atmospheric path radiance is constant over the entire image, and if the enhanced HR image is going to be used for visual interpretation rather than to derive secondary remote sensing products. The best correction when physical units are needed is to model the atmosphere with a radiative transfer code, as discussed in Sect. 5.3.

Figure 5.3: The original “Isotopes” MTI image (upper left) and the three-look images with modeled atmospheric path radiance (upper right at -50° , lower left at 0° , and lower right at $+50^\circ$).

Figure 5.4: The HR estimate for $\theta = -50^\circ, 0^\circ, +50^\circ$ without atmospheric correction. The different contrast in the LR frames prevents POCS from giving good results. The ISNR is 2.07 dB.

Figure 5.5: The ISNR for three-look imagery with uncorrected atmospheric path radiance, using different off-nadir angles.

Figure 5.6: The HR estimate with the bias subtracted from the LR frames to compensate for off-nadir atmospheric path radiance. The pixels in the baseball field no longer look speckled, however some artifacts remain due to the large off-nadir imagery at $\pm 50^\circ$. The ISNR is 2.79 dB here, an improvement of 0.72 dB over the uncorrected case.

Next, the effects of directional reflectance are examined. The “Isotopes” image contains a baseball field that is composed of grass turf. To simulate the effect of BRDF on the resolution enhancement, the pixels composing the field are scaled to simulate the change in radiance expected at off-nadir angles. The simulated BRDF-scaled images are input to the POCS algorithm and the ISNR is computed. The BRDF scaling used is taken from a study by Sandmeier, et al. [69] that measured the reflectance of a grass lawn in the laboratory using a transportable field goniometer (FIGOS). The data were provided in a graph of bidirectional reflectance factor (BRF) versus view zenith angle; for this experiment, the values were measured from the graph and stored in a lookup table of BRF vs. angle, so the values are approximate. The BRF R is the ratio of the reflected energy from a material of interest to the energy that is reflected from an ideal Lambertian surface. A Lambertian surface is one that reflects energy equally in all directions, or

$$L_{reflected} = \frac{\rho E_{incident}}{\pi}, \quad (5.7)$$

where L is radiance in Watts/m²/sr, E is the incident irradiance from the sun, and ρ is the reflectance. The BRF is given by

$$R = \pi f_r = \frac{\Phi_{sample}}{\Phi_{lambertian}}. \quad (5.8)$$

To scale the grass baseball field pixels to model BRDF effects, the BRF at the view angle of an off-nadir image is found in the lookup table, then the BRF at nadir is

found. The ratio of the BRFs provides the scale factor for the grass pixels:

$$\Phi_{sample}(\theta_o) = \frac{R(\theta_o)}{R(\theta_n)} \Phi_{sample}(\theta_n). \quad (5.9)$$

Table 5.1 summarizes the measured BRF values as a function of view angle in the principal plane for grass at 550 nm, along with the scaling factor $S = R(\theta_o)/R(\theta_n)$ applied to simulate the off-nadir BRDF effect.

$\theta[^\circ]$	BRF	S
-30.0	0.062	0.886
-25.0	0.060	0.857
-20.0	0.062	0.886
-15.0	0.064	0.914
-10.0	0.066	0.943
-5.0	0.068	0.971
0.0	0.070	1.000
5.0	0.074	1.057
10.0	0.080	1.143
15.0	0.085	1.214
20.0	0.092	1.314
25.0	0.100	1.429
30.0	0.115	1.643

Table 5.1: The view angle and corresponding BRF and scaling factor for grass turf at 550 nm.

Figure 5.7 shows the HR estimate for the three-look case at $\theta = -20^\circ, 0^\circ, +20^\circ$. Ringing is visible along the edges of the baseball field, indicating inconsistent data due to the BRDF effect. The ISNR curves for the three-look imagery with uncorrected BRDF effects are shown in Fig. 5.8. For $\theta > 20^\circ$, the POCS algorithm starts to diverge. Note that BRDF results will vary depending on the type and amount of non-Lambertian material. However, these results indicate that if highly

non-Lambertian materials are in the scene that is to be resolution-enhanced, then BRDF correction may be necessary.

Figure 5.7: HR estimate with BRDF effects for $\theta = -20^\circ, 0^\circ, +20^\circ$.

Figure 5.8: The ISNR for three-look imagery with uncorrected BRDF effects, using different off-nadir angles.

CHAPTER 6

CONCLUSIONS

This dissertation showed that multiframe resolution enhancement algorithms can quantitatively and qualitatively improve the spatial resolution of images from a remote-sensing imaging system by combining sequences of multi-look images. A simulation tool was developed that allowed the modeling of off-nadir imagery. The multi-look image simulation tool was based on a Fourier-optics-based sensor model and modeled the sensor viewing geometry with a projective transform, using the basic sensor platform parameters of the Multispectral Thermal Imager (MTI). The multi-look image simulation tool was used to generate two-look, three-look, and multi-look imagery of a standard image-processing test image and of an image acquired by the MTI. The Projection Onto Convex Sets (POCS) resolution enhancement algorithm was implemented with standard data consistency and amplitude-bound constraints and applied to the simulated multi-look imagery. The effects of aliasing in a sensor system were modeled to test the POCS algorithm under a range of aliasing conditions. Data from a multispectral microscope were used to demonstrate how POCS may be used to improve the resolution of multispectral imagery. Finally, atmospheric path radiance and directional reflectance effects were modeled to determine their effects on POCS resolution enhancement.

6.1 Major findings

If the sensor is configured to acquire imagery with symmetric view angles in at least a set of three, with one forward-pointing off-nadir image, one nadir image, and one backward-pointing image, the resolution is optimally enhanced. The ideal is to acquire as many images as possible, as close to nadir as possible, and within as short a time as possible. Practical constraints on the number of images that may be acquired during one overpass limit the resolution improvement that is possible for remotely-sensed imagery.

Images acquired too far off-nadir can lead to divergence of the POCS algorithm. For the simulated images here, using views farther than 48° off-nadir were counter-productive for this reason.

From the “Isotopes” simulations here, three symmetric LR frames can improve the imagery by 7.5 dB when restored on a grid twice the size of the LR frames. Seven images can provide an improvement in SNR of 9.5 dB, while six images give a 8.2 dB improvement. The “Cameraman” results are similar: three symmetric frames give an ISNR of 7.1 dB, six asymmetric frames give an ISNR of 8.6 dB, and seven asymmetric frames give an ISNR of 10 dB. Using more than seven asymmetric frames did not improve the ISNR results.

Atmospheric and BRDF effects also should be considered when combining multi-angle images. Atmospheric correction is needed when $\theta > 40^\circ$, and directional

reflectance prevents convergence of POCS when $\theta > 20^\circ$. Thus, the LR frames should be acquired at small angles, or $\theta \leq 20^\circ$.

The aliasing present for a given sensor band also affects how much resolution increase can be expected. Aliased images benefit the most from resolution enhancement processing, since they provide imagery with different details. Non-aliased images are difficult to improve as they already are of high quality.

Although not studied here, the registration of the LR images is also critical for good resolution improvement.

6.2 Directions for future research

A Gaussian estimated system PSF was used in the POCS algorithm implementation in this dissertation. The elliptical Gaussian system PSF approximation was chosen because it has been previously used for remote sensing resolution enhancement, it is easily computed for off-nadir imagery by scaling by the appropriate factor of cosine separately for the along-track and cross-track directions, and its affine mapping from the LR frame to the HR estimate grid is simple to compute, thus avoiding the time-consuming computation of a projective mapping for each LR pixel. The Gaussian width, or standard deviation, was chosen to account for both the optics and detector subsampling. The Gaussian function smoothly rolls off; for a detector-limited sensor, the shape of the Gaussian is not the best approximation for the system PSF. However, a function that can be mapped with an affine

transform is important for keeping the processing time reasonable. For the strongly detector-limited case, it may be possible to use an indicator function (rectangle) and get acceptable results. Due to the sensitivity of the results on the choice of the Gaussian PSF width σ , this issue is clearly important for further research.

The sensor model in this dissertation only included the effects of the optics and detectors. Refinements of the model would be valuable to study the effects of other system components on the POCS resolution enhancement results, including the PSF due to image motion, the electronics PSF, and sensor noise. The detectors here were modeled simply as a 2D CCD array rather than line detectors with variable integration times, as is the case for the MTI. The detector fill factor (spacing between detectors) was neglected as well. In addition, the image geometry could be better modeled. Sensor pointing in the cross-track direction was neglected; many sensors can point “to the side,” allowing acquisition of targets in the previous or next orbital track of the satellite. Using these images would increase the total number of LR frames available to the POCS algorithm, and thus improve the HR estimate. In addition, the surface of the earth is not flat, as was modeled here, and terrain and elevation were not considered.

The POCS algorithm is only exceeded in popularity by Bayesian image resolution enhancement methods. The Bayesian approach was not considered here because it did not appear to be appropriate for remotely-sensed imagery in previous research [37]. However, Bayesian methods do provide additional constraints that

can prevent the ringing observed in enhanced imagery when the sensor is nearly Nyquist-sampled. Recent reviews [7] have indicated the possibility of combining POCS with the MAP Bayesian approach to form a hybrid resolution enhancement algorithm. Thus, the performance of hybrid image resolution enhancement methods for systems with and without aliasing would be a good avenue to explore for enhancement of remote sensing imagery as well as for other types of imagery.

Appendix

RADIOMETRIC TERMS

It is helpful to define some radiometric terms that may be used in the dissertation.

- The *radiant energy*, Q [Joules], is the energy traveling in the form of electromagnetic waves.
- The *radiant flux*, Φ [Watts = Joules/sec], is the rate at which radiant energy is transferred from a point on a surface to another surface.
- The *radiance*, L [W/m²/sr], in a given direction at a point on the surface being sensed, is the radiant flux leaving an element of the surface surrounding the point and propagated in directions defined by an elementary cone containing the given direction, divided by the product of the solid angle of the cone and the area of the orthogonal projection of the element of the surface on a plane perpendicular to the given direction [70]. It is given by

$$L = \frac{\partial^2 \Phi}{\partial \Omega \partial A \cos \theta}.$$

- The *reflectance*, ρ , is the ratio of reflected radiant flux to incident radiant flux,

$$\rho = \frac{\Phi_r}{\Phi_i}.$$

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