MODULATION TRANSFER FUNCTION COMPENSATION THROUGH A MODIFIED WIENER FILTER FOR SPATIAL IMAGE QUALITY IMPROVEMENT

by

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LIST OF ABBREVIATIONS

2D	-	Two-Dimensional
CCD	-	Charge-Coupled Device
DN	-	Digital Number
EOS	-	Earth Observation Satellite
ESF	-	Edge Spread Function
EM	-	Expectation-Maximization Algorithms
ETM+	-	Enhance Thematic Mapper
FWHM	-	Full Width Half Maximum
GCP	-	Ground Control Points
GCV	-	Generalized Cross-Validation
GSD	-	Ground Sample Distance
IFOV	-	Instantaneous Field Of View
LSF	-	Line Spread Function
MSE	-	Mean Square Error
MTF	-	Modulation Transfer Function
MTFA	-	Modulation Transfer Function Area
MTFC	-	Modulation Transfer Function Compensation
NRME	-	Normalize Root Mean-Squared Error
OTF	-	Optical Transfer Function
PDF		Probability Density Function
PSF	-	Point Spread Function
PSNR	-	Peak Signal-To-Noise Ratio

PTF	-	Phase Transfer Function
RL	-	Richardson–Lucy
SDP	-	Science Data Purchase
SNR	-	Signal to Noise Ratio

LIST OF SYMBOLS

*	-	Conjugate
•	-	Convolution
$\cdot$	-	Multiplication
β	-	Inverse control parameter
λ	-	Regularization parameter
γ	-	Smooth control parameter
σ	-	Standard deviation

PEMAMPASAN FUNGSI PEMINDAHAN MODULASI MENERUSI PENAPIS WIENER YANG DIUBAH-SUAI BAGI MEMPERBAIKI KUALITI IMEJ SPATIAL.

ABSTRAK

Kebergunaan data imej yang diperolehi dari suatu sensor pengimejan amat bergantung kepada keupayaan sensor tersebut untuk meresolusikan perincian spatial ke satu tahap yang boleh diterima. Keupayaan tersebut, akan menentukan kualiti imej dari segi kejelasannya. Salah satu cara untuk mengukur pencapaian sesebuah sistem pengimejan dan juga kualiti sesebuah imej adalah dengan menentukan fungsi pemindahan modulasi (FPM) bagi sistem tersebut. FPM adalah satu metrik pengukaran kualiti yang sering digunakan dalam bidang pencerapan jauh. Ia ditakrifkan sebagai magnitud ternormal untuk transformasian Fourier *(Fourier Transform)* bagi fungsi sebaran titik (FST) yang dimiliki oleh sesebuah sistem pengimejan. Kesan integrasi FST untuk sesebuah sistem pengimejan boleh menjejaskan ciri-ciri tertentu dalam sesebuah imej. Penerbitan FST dari pinggir yang linear pada suatu imej boleh dianalisa untuk menterjemahkan FPM dalam domain frekuensi. Pengetahuan dan pemahaman ke atas FPM membolehkan satu taksiran dibuat secara objektif bagi menilai pencapaian sistem pengimejan dan operasi pemprosesan dengan tujuan untuk memulihkan degradasi imej. Dalam penyelidikan ini, satu teknik projeksi pinggiran berfideliti tinggi yang tak-varian kepada sudut pinggiran telah dibangunkan untuk mendapatkan pengukuran FPM. Teknik ini mampu menghasilkan keputusan pengukuran yang tepat dan tidak-bias. Ukuran FPM telah digunakan untuk pemodelan fungsi degradasi dan kemudiannya diaplikasikan menerusi penapis Wiener yang telah diubah-suai untuk pemulihan imej. Kaedah regularisasi telah digabungkan dengan penapis tersebut untuk mengatasi

masalah *ill-posed* dalam pemulihan imej. Percubaan tersebut menampakkan peningkatan kualiti imej yang ketara. Teknik Pengukuran dan pemampasan FPM yang dicadangkan ini membentuk satu sistem bersepadu yang dapat mengukur FPM bagi pencirian kualiti sistem pengimejan dan peningkatan kualiti imej spatial. Set data yang digunakan dalam analisis ini adalah imej pencerapan jauh yang diperolehi dari produk Level- 2A bagi IKONOS dan telah dikabur secara sintetik. IKONOS merupakan sebuah satelit komersial bagi pencerapan bumi yang mempunyai keupayaan pengimejan imej beresolusi tinggi dengan kira-kira satu meter resolusi dalam jalur pankromatik.

MODULATION TRANSFER FUNCTION COMPENSATION THROUGH A MODIFIED WIENER FILTER FOR SPATIAL IMAGE QUALITY IMPROVEMENT

ABSTRACT

The usefulness of image data acquired from an imaging sensor critically depends on the ability of the sensor to resolve spatial details to an acceptable level. This ability, in turn, will determine the image quality in terms of sharpness. A way to describe the performance of an imaging system and the quality of an image is to specify its modulation transfer function (MTF). The MTF is a system quality metric that is often used in remote sensing. It is defined as the normalized magnitude of the Fourier Transform of the imaging system's point spread function (PSF). The integrating effect of the PSF of an imaging system affects the signature of a feature in the image. Derivations of PSF from a linear step-edge in the image can be analyzed to interpret the MTF in frequency domain. Knowledge of MTF enables an objective assessment of imaging system performance and preprocessing operation to compensate for the image degradation. In this research, a high fidelity edge projection technique which is invariant to edge angle was developed to obtain the MTF measurements. The technique can produce a precise and unbiased measurement. The MTF measurements were used to model the degradation function and subsequently applied through a modified Wiener filter for image restoration. Regularization method has been incorporated in the filter to overcome its ill-posed problem from restoration. This attempt results in a significant improvement in terms of image quality. The proposed MTF measurement and compensation technique formed a unified system that measures MTF for imaging system

quality characterization and spatial image quality improvement. The results by the system were analyzed and presented, they were found to be consistent. The data sets used in the analysis were synthetically blurred remotely-sensed images simulated from Level-2A, a product from IKONOS, a commercial remote sensing system satellite with imaging capability of high resolution image of approximately one meter ground sample distance in panchromatic band.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Imagery from orbiting satellite sensors provides geophysical and biophysical information about the earth's terrestrial and oceanic characteristics and the effects that human activities have had upon them. To ensure users that the satellite's imagery is reliable and suitable for particular use or research, quality assurance in remote sensing data processing must be in place. For remote sensing quality assurance to be optimal and widely applicable operationally, it should include the fundamental steps of calibration and validation. Before an earth observation satellite is launched into orbit, *pre-flight calibration* should be conducted to characterize the radiometric performance[1] of the satellite's imaging sensors. Once the satellite is in orbit, *in-flight calibration* should be carried out to validate the performance of the satellite's imaging sensors and the quality of the remotely-sensed data (Chen, 1996).

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[1] **Radiometric performance** of an imaging system describes the ability of the system to respond to various input radiance levels.

Optical imaging sensors are typically designed with the capability to scan multiple wavelengths, including visible light, near infrared, middle infrared and thermal infrared, depending on the requirement. They remotely produce images in a panchromatic[2] band and a multispectral band. Remotely-sensed imagery is typically noisy, with vague edge and brightness content. Many image processing and analysis techniques have been developed to aid the interpretation of these images in order to extract as much information as possible from the images. Prior to data analysis, the raw data is processed to correct any distortion due to the characteristics of the imaging system and imaging conditions (Chen, 1996). Depending on the user's requirement, some standard correction procedures may be carried out by the operators at the ground receiving station before the data is disseminated to the end user. These activities are part of the calibration and validation process.

Spatial image quality is one of the key parameters for characterizing and validating image data (Chen, 1996). It is important to appreciate the spatial characteristics of image data, particularly if the data is to be used for image analysis. The technical characteristics of image data must be well understood before image analysis can be done, since the quality of the analysis depends on the quality of the data.

[2] **Panchromatic** band is acquired with a sensor that is sensitive to all or most of the visible spectrum and offer a finer resolution than other bands. It is normally shown in black and white

1.2 Motivation and Background

RazakSAT™, Malaysia's own small satellite that was launched onboard the Falcon 1 on the 14th of July, 2009, is an earth observation satellite (EOS) with high spatial resolution imaging capability, which offers Malaysia its own platform for remote sensing capabilities. A processing technique for image assessment and enhancement is essential to assure the product's quality.

The usability of images for interpretation, registration or object reconstruction purposes highly depends on the image quality. In principle, there is no difference of whether image analysis is performed manually or automatically, since the reliability, accuracy and precision of the results of image analysis procedures are strictly influenced by the quality of the underlying image data. Image quality can be characterized by the image's radiometry, which can be measured by a vast number of factors, such as contrast, brightness, noise variance, sharpness, radiometric resolution, granularity, modulation, contrast transfer function and many more (Erin, 2004).

Among other measures, image sharpness is vital for characterizing images, for much of the information of an image resides in its edges. Image blurriness, which limits the visibility of details, can be objectively measured by the point spread function (PSF), or its amplitude spectrum, which is the modulation transfer function (MTF). The MTF describes the attenuation of sinusoidal waveforms as a function of spatial frequency (Kohm, 2004). Practically, MTF is a metric quantifying the sharpness of the reconstructed image. Knowledge of the MTF for a given image acquisition system is fundamentally important since it enables an objective assessment of the imaging performance and can be utilized through image restoration techniques to restore the sharpness of a blurred image.

In image restoration, if the degradation is a linear, position-invariant process, then the blurred image (degraded image) can be described in the spatial domain by

$$g = Hf + \eta \tag{1.1}$$

where g represents the degraded image, f represents the original image, matrix H represents the degradation function, and η represents the additive white noise. Note that degradation is modeled as being the result of convolution. The restoration seeks to find filters that apply the process in reverse. The term *image deconvolution* is used frequently to signify image restoration. Similarly, the filters used in the restoration process are often called deconvolution filters. The Fourier transform of degradation function H is referred as the MTF (Umbaugh, 2005). Hence, in this research, MTF will represent the matrix H (Shacham *et al.*, 2007), and will be used through a deconvolution filter to restore the degraded image.

Spatial image degradation can happen in many ways. For satellite imaging, image acquisition occurs while orbiting the earth, and due to the satellite's altitude determination control for maneuvering, the instantaneous field of view[3] (IFOV) of the imaging system can be greater or lesser than the nominal resolution at any point in time

[3] **Instantaneous Field of View (IFOV)** is defined as the angle subtended by a single detector element on the axis of the optical system(Schowengerdt, 2007)

during image capturing. This results in MTF degradation proportional to the ratio of IFOV and Ground Sample Distance[4] (GSD) during image acquisition (Frank, 2000). Moreover, regardless of how well an image system is fabricated, it will inevitably suffer from some degree of blur. These sorts of degradations need to be compensated, and they can be compensated using the MTF as a degradation function for that image restoration. For this purpose, a method for image quality characterization and improvement through MTF Compensation (MTFC) is proposed for this research.

Image quality characterization using MTF is fairly new in the field of optical engineering. It has been used by several orbit EOS, such as IKONOS (Helder & Choi, 2002) and Orbview (Kohm, 2004), among others. Until recently, this approach was still considered the best approach to quantify the spatial image quality of a remote sensing imaging system. The THEOS (THailand Earth Observation Satellite), which was launched on the 1st of October, 2008, (Nutpramoon *et al.* 2007) proposed to use this approach. Image quality improvement through the knowledge of MTF, commonly referred to as MTFC, is available as a processing option for in-orbit EOS. This MTFC restoration filter is not published, as it is considered to be a proprietary "value-add" tool for commercial products (Schowengerdt, 2007).

[4] In remote sensing, **ground sample distance** (**GSD**) is the spacing of areas represented by each pixel in a digital photo of the ground from air or space. GSD is a measure of one limitation to image resolution, that is, the limitation due to sampling (Leachtenauer and Driggers, 2001).

1.3 Problem Statement

An imaging system of a satellite modifies the spatial properties of a scene under two circumstances: when there is blurring due to characteristics of the system optics, detectors, and electronic components, or when there is distortion of the scene geometry due to the motion of the imaging system during image acquisition. The effects of blurring and distortion have always been a big concern in image processing and vision-based systems. Blurred images inherently have less information than sharp images, which leads to difficulty when performing image analysis and scene interpretation. The problem of blurring and distortion is that they degrade the satellite image quality, and these sorts of degradations can and need to be compensated. Blurring and distortion caused by the system imaging optics and motion of the imaging system during acquisition may be estimated from the images. These properties are useful in designing a compensation system to remove the blur and distortion, thus these properties will be investigated to produce a high representation of PSF profile and its interpretation in frequency domain, which is the MTF in order to produce a robust MTF measurement technique, which in turn will produce a robust MTFC technique.

The major goal of existing MTFC is to partially compensate for the system response by boosting the attenuated higher spatial frequencies. This attempt enhances fine spatial detail but unfortunately, it has the side effect of increasing the image noise. In other words, it reduces the image's Signal to Noise (SNR), which is another means for image quality assessment. Figure 1.1 illustrates the satellite images, where Figure 1.1 (a) is the original raw image that shows distortion of scene geometry and blurring, while Figure 1.1.(b) shows improvements that can be seen with existing MTFC techniques (U.S. Geological Survey, 2005). However the improvement also results in a grainy appearance. With this limitation, the relative importance of image sharpness versus noise to the applications is left to the user to decide whether MTFC processing is appropriate. From this viewpoint, it is obvious that a new method that incorporates both deblurring and denoising techniques is necessary for the research problem. The problem of deblurring and denoising of imaging data is typically called image restoration. This research will propose an efficient MTFC technique which shall be robust to noise; robustness to noise in this case refers to the ability of the algorithm to suppress noise amplification that results from restoration technique.


(a)


(b)

Figure 1.1: Illustration of satellite images before and after preprocessing using existing MTFC (courtesy of U. S. Geological Survey, 2005)

The main research question triggered from the above statements is "***How** to produce a **more effective MTFC technique** that can **invert blurring** while simultaneously **preventing noise amplification** for spatial image quality improvement?*"

The sub questions of the main research questions are as follows:

i. How to compute degradation function from the images? And how can these properties be used to characterize an imaging system and design an image degradation compensation system?

ii. Why the existing MTFC (Boggione & Fonseca, 2003; Lee *et al.*, 2008) has a side effect of increasing image noise? And how to overcome this side effect in order to produce an MTFC technique that sharpens images without compromising noise?

iii. What are the quality metrics for defining spatial images? And how to verify that a particular MTFC technique actually improves spatial image quality?

1.4 Research Objective

The main objectives of this research are:

(a) To propose an Edge Spread Function (ESF) projection technique that is invariant to edge angle in order to produce a high fidelity representation of ESF profile for MTF measurement that

- effectively characterizes the spatial performance of the in-flight satellite imaging system; and
- represent the exact image degradation function which then be used to design an MTFC filter.

(b) To investigate the problem of image noise amplification in the existing MTFC for remotely-sensed image restoration, in order to propose an efficient MTFC technique that executes an optimal tradeoff between sharpness and noise which

- warrants an acceptable result of image restoration; and
- will significantly improve spatial image quality of high resolution satellite images.

1.5 Research Scope

This research focuses on remote sensing data, which are the remotely-sensed images. In this research, the focus is only on data in a panchromatic band. Typically, validation of the performance of a satellite imaging sensor and the quality of the remotely-sensed images rely on key parameters, such as the geometric accuracy, radiometric accuracy and spatial quality. However, in this research, the focus of interest is the spatial quality.

As mentioned earlier, image quality can be characterized by a large number of measures, but among all measures, the research scope focuses on image sharpness. Characterization of an image based on sharpness highly depends on information that resides at the edges, so during data collection, the focus shall be on images with a high-contrast and homogenous edge target. Simulation by Helder and Choi (2002) suggests that homogenous targets with SNR greater than 50 are ample for acceptable end results.

Degradation comes in many forms such as blurring, noise, and distortion. However, this research concentrates on compensation of degradation of spatial properties of images caused by blurring only.

1.6 Research Contribution

A robust MTF measurement technique is important to provide a high-precision, reliable way to assess the performance of the in-flight satellite imaging system. Moreover, the MTF calculation from the MTF measurement technique can be utilized through image restoration techniques to compensate the degraded satellite image. The restoration filter should be robust, meaning it should execute an optimal tradeoff between sharpness and noise in the restored image. Hence, the main contributions of this proposed research are to develop a robust MTF measurement technique through a high fidelity Edge Spread Function projection to characterize the performance of a satellite imaging system, and to develop a robust restoration technique through MTF compensation and regularization concepts to restore the sharpness, which in turn will improve the quality of the high resolution satellite images.

Image quality characterization through MTF measurement as proposed above shall be utilized as a validation process in assessing the quality of the data products derived from RazakSAT™. Thus far, there has been no research measuring image quality for an on orbit sensor in Malaysia. This work is the first attempt and shall be initiated to characterize the MTF of the RazakSAT™ system during commissioning and continuing throughout the life of the program. In addition, the restoration technique can be incorporated in the Imaging Receiving and Processing System of RazakSAT™ at the ground station located at the Malaysia Space Center as an image reconstruction technique during image acquisition.

1.7 Organization of Thesis

This thesis consists of seven chapters as follows:

Chapter 1 briefly states the introduction of the research, the motivation and the research background. The discussion includes the problem statement, research hypotheses and research scope, which define the research objectives. Finally, the potential research contributions by this research are stated.

Chapter 2 reviews the relevant research on techniques available for image sharpness and the image restoration that can be used to develop an MTFC filter. Also, relevant research on MTF Measurement techniques is reviewed. All available techniques are categorized and discussed in detail. Discussion and revision on the merits and drawbacks of the techniques are revealed.

Chapter 3 discusses theoretical issues that form an important background of the proposed method for this thesis. Discussions are on the relevant theory of imaging systems, with emphasis on a description of linear position-invariant systems, impulse response of an imaging system, and a description of measures that represent the quality of an imaging system. Also, relevant theory of image selection and optimal selection of regularization parameters are briefly discussed.

Chapter 4 presents the research procedure, theoretical framework and justification of the research problem. The discussion in research design focuses on data collection methods and data analysis. The remaining part of the chapter includes the research limitations and assumptions.

Chapter 5 details out the proposed method that will be used in this research. All the techniques and approaches that are required in the proposed method are discussed. The proposed modified deconvolution filter is explained in detail at the end of the chapter.

Chapter 6 presents the results acquired in this research and their evaluation. It also includes a thorough discussion of the results. The hypotheses that are formulated for the research are analyzed and presented at the end of the chapter.

Chapter 7 summaries and concludes the results from the evaluation in Chapter 6. The fulfillment of the goal of this research and its contributions is reviewed. Finally, the thesis is concluded with ideas for future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

There are a few ways to improve corrupted image quality caused by degradation, such as blurriness. Since a lot of information can reside in every edge of an image, its sharpness is very important to the visual quality. Edge sharpening techniques are a way to solve image degradation. In many ways, image restoration, which aims to "compensate for" or "undo" defects that degrade an image, has been studied (Campisi & Egiazarian, 2007) as a treatment of degraded images. Image restoration draws researchers from many disciplines, including mathematics, astronomy, computer science, and remote sensing, as well as several branches of engineering and medicine. As a result, a diverse variety of approaches has evolved. Deconvolution is particularly important in image restoration. Image restoration is fundamentally an **ill-posed problem**[5], thus it requires sophisticated mathematical and statistical analyses to regularize the problem (Chantas *et al.*, 2008). This method is called the Regularization method.

[5] **Ill-posed problem** is a problem whose solution is not unique and/or does not exist for any data and/or does not depend continuously on the data. (Bertero and Boccaci, 1998).

This chapter consists of two main discussions. The first discussion explains the literature review of various solutions to image degradation. They comprise of edge sharpening techniques that emphasize Ramp width reduction filters (Leu, 2000) and image restoration techniques that include the Deconvolution and Regularization method. The second discussion presents the literature review of existing methods for MTF measurement and MTF compensation.

2.2 Edge Sharpening

In image quality assessment, sharpness is not the only important factor, but arguably the most important factor. It is the most closely related factor to the amount of detail that an image can render. Sharpening of images is a classic problem in image processing. It can be approached with two types of operation: point operation and neighborhood operation. In point operation, it is done by mapping each intensity level of a new value according to the shape of the original histogram of the image under test (Hummel, 1977). The most popular method of this type is histogram equalization. However, this approach produces good results only when the image does not require the utilization of full intensity range, therefore it is not applicable to all images. Besides, it may result in noise amplification and produces unnatural appearances when the intensity range of a largely homogeneous region is stretched (Leu, 1992; Raji *et al.*, 1998). Yoon and Song (2007) proposed a generalized histogram with fractional count, it is done by adjusting the fractional count for each pixel according to user's requirement and its spatial activity, the amount of contrast enhancement is controlled appropriately to human observers. They claimed that the proposed method achieved visually more natural appearance than conventional histogram equalization methods.

Between these two operations of image sharpening, the neighborhood operation is the simplest and most widely adopted. It is done by raising the intensity of the brighter side of an edge while lowering the intensity of the darker side. Usually, it requires a sharpening kernel to perform spatial filtering over the image under test. Unsharp masking filter (Jain, 1989) is one of the popular filters. The drawback of this filter is the over adjusted intensity of both the brighter side and darker side of the edges; it produces over-shoots along both sides of an edge that causes a ringing effect. To overcome this problem, researchers have used quadratic filters (Guillon *et al.*, 1998), cubic filters (Ramponi, 1998), and filters based on order statistics (Lee & Fam, 1987). However, it cannot avoid noise increment of the image, which in turn is the major drawback of these filters. Some researchers have proposed adaptive approaches to use different filter for each part of an image (Centeno & Haertel, 1997).

The most commonly adopted approach in the previously mentioned method works by increasing the contrast of the edges to achieve sharpening. This operation mainly increases the difference of intensity across an edge, but in a way, the width of the edge remains unchanged. This method might be effective for sharpening narrow and low contrast edges, for edges which are wide and blurry, the sharpening effect is limited. Hence Leu, (2000) proposed different concept of neighborhood-based operation for image sharpening which sharpens an edge by reducing its width. This method is called the Ramp width reduction filter, its result can be analogous to when one adjusts the focus of a camera in order to bring an edge into focus; the effect is to reduce the edge's width. The edge's width is adjusted based on three intensity indices (I_H, I_M and I_L) and three gradient indices derived from the Sobel operator. Three intensity indices is used to determine whether the pixel is on the intensity ramp ($I_H > I_M > I_L$) as illustrated in figure 2.1, whereby the three gradient indices is used to specify the location of the pixel relative to the centerline of ramp.

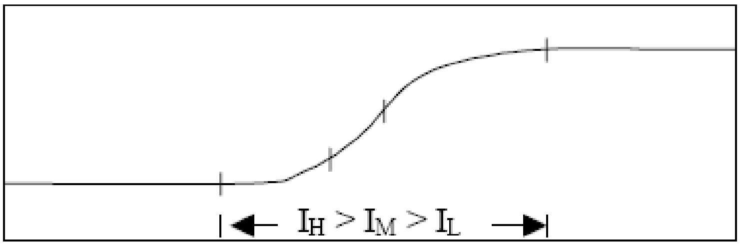

Figure 2.1: A typical ramp edge (Leu, 2000)

The intensity of the pixel under test is adjusted based on its location as follows:

i. If it is located above the centerline on the ramp, the pixel's intensity will be increased;

ii. If it is located below the centerline on the ramp, the pixel's intensity will be reduced; and

iii. If it is on or near the ramp's centerline, the pixel's intensity unchanged.

With this way the width of the ramp edge may be reduced and the edge becomes sharper. Ramp width reduction was used by Patra *et al.* (2002) as a comparative method to their proposed MTFC for image quality improvement. The drawback of this method is the integrity of true edge localization, for it is not robust to noise; the addition of noise to an image caused the position of the detected edge to be shifted from its true location.

Using edge sharpening techniques is one way to enhance an image. As with any image enhancement, the ultimate goal of restoration is to improve an image in some predefined sense, making it a largely subjective process (Gonzalez and Woods, 2002). The next section discusses an alternative solution to image degradation.

2.3 Image Restoration

Image restoration is an objective process where the ultimate goal of restoration is to recover a degraded image by using *a priori* knowledge of the degradation phenomenon. The theoretical background of this approach is presented in chapter 3. Restoration techniques find filters that apply inverse process in order to recover its original image. It is an inverse problem and the filters used in this process often called Deconvolution filters. In image restoration, the main challenge is to prevent noise of input data from being amplified to unacceptable artifacts in the restored image. Since deconvolution is in image restoration, it is ill-posed and usually will not have a unique solution, even with the absence of noise (Kundur & Hatzinakos, 1996). Nevertheless, it is possible to regularize the solution by introducing *a priori* constraints. In image restoration, the basic idea of regularization methods is to truncate, or to dampen the spectral decomposition of the solution before the small singular values start to dominate (Bertero & Boccacci, 2002). A comprehensive explanation of regularization method is presented in chapter 3. This thesis proposes a robust MTFC filter that employs the concept of deconvolution and regularization method.

2.3.1 Deconvolution

The term "*deconvolution*" according to Jain and Ranganath (1981), it refers to the process of reconstructing the original image from either one or multiple degradation observation, using the information about the imaging system and the original image. In most situations, the Point Spread Function (PSF) which is the degradation function is assumed to be known explicitly prior to the deconvolution procedure. This problem is known as the classical linear image restoration problem (Kundur & Hatzinakos, 1996). This, however, is almost never the case in practical imaging situations, as the blur is often unknown, with limited information about the true image. Therefore, the original image must be identified directly from its degraded image by using partial or no information about the blurring process and the true image. Such an estimation problem, assuming the linear degradation model of equation (1.1), is called *blind image deconvolution* (Kundur & Hatzinakos, 1996; Shacham *et al*., 2007).

There has been extensive work on *blind deconvolution* over the past 20 years, Kundur and Hatzinakos (1996) categorized the existing *blind deconvolution* methods into two major classes based on the adopted approach; *direct blind deconvolution* method and *iterative blind deconvolution* method.

2.3.1(a) Direct Blind Deconvolution

Direct Blind Deconvolution works by estimating the PSF separately from the true image, and treat both the PSF and true image as a disjoint procedure from the restoration algorithm. It is based on the assumptions that the characteristic of PSF is circularly symmetric, and the availability of a known parametric form of the blur. Since it is directly fed to one of the known classical deconvolution filter and solves in just one-step, this leads to computationally simple algorithms. Chalmond (1991) is one of the examples. In his works, he proposed to estimate PSF from sharp edge elements in the image, and with the underlying assumption that the shapes of all the extracted edges can be modeled as ideal step functions in the ideal image. Thus, it has a main drawback when no criterion is employed to evaluate the extracted step-edge from the set of sharp edge elements of the degraded image. The most commonly used deconvolution filters in *direct blind deconvolution* are the Inverse filter (Gonzalez & Woods, 2002; Boggione & Fonseca, 2003) and Wiener filter (Bretschneider, 2002; Gonzalez & Woods, 2002; Lee *et al.*, 2008).

Li and Merserau (2005) proposed a direct blind deconvolution method for identifying a parametrically described blur based on kurtosis minimization. In their work, different choices for the blur parameters were used with a Wiener filter to restore the noisy blurred image. Kurtosis is a parameter that describes the shape of a random variable's probability density function (PDF). It is used by Li and Merserau (2005) as a measurement for the quality of the restored images. The main disadvantage of this method is the requirement for *a priori* knowledge of the blur parameter range for a reasonable computational load.

Recently, a *direct blind deconvolution* method for atmospheric blurring in long-distance imaging (astronomy) based on automatic best step-edge detection has been proposed by Shacham *et al.* (2007). This method overcomes the issue of Li and Merserau (2005). It is based on the assumption that atmospheric blurring is an isotropic degradation; an isotropic PSF that does not require a known parametric model. The algorithm includes Canny edge detection operation (Canny, 1986) in the first stage to produce a single line edge. In the second stage, the straightness and the length of detected edges are evaluated. The best edges obtained in this stage are then evaluated by having the properties of homogenous areas from both sides and high contrast, which characterizes a step edge. The Edge Spread Function (ESF) is estimated by taking step-edge vectors along the edge direction. The edge direction relatives to the images axes that is calculated by the inverse tangent of the step-edge's vertical derivation divided by its horizontal derivative. The edge is rotated according to its angle to form a vertical approximation of the step-edge. The atmospheric PSF whose Fourier transform magnitude is the MTF is derived from it to restore the degraded image using Wiener filter, given by

$$W(u,v) = \frac{1}{H(u,v)} \cdot \frac{|H(u,v)|^2}{|H(u,v)|^2 + \alpha} \qquad (2.1)$$

where *u* and *v* are the spatial frequency coordinates, H(u,v) is the MTF, and α is the ratio between the spectrum of the noise and the original image. The ratio is not known, so Shacham *et al*., (2007) assumed it to be a constant proportional to the inverse o f Signal to Noise (SNR) of the image. This paper emphasized on image restoration which involved the MTF compensation. Therefore results of the MTF measurement in term of Full Width Half Maximum (FWHM) of the PSF and MTF at *nyquist* frequency were not presented. Two result examples of MTF compensation were presented in this paper, one of them is a synthetically blurred image, and the other one is a real degraded image. The restoration quality was measured using the ratio between the areas under the MTF curve after and before restoration. The measured ratios are reported as 2.31 and 1.71 for the synthetically blurred image and the real degraded image, respectively. These results demonstrated that the proposed method by Shacham *et al.* (2007) was effective to restore degraded image. The main novelty in their works is the automatic extraction of such a step-edge. This could be the merit of this method as heuristic search for step-edge would be very tedious and not practical in applications where computation time is taken into consideration. However it could be the pitfall for this method, as the criteria employed in this method include the straightness, length and magnitude of the edge, and also the homogeneity of the step. The accuracy of the estimated PSF highly depends on these criteria. Since automatic extraction of step edge using canny edge detection is slightly sensitive to weak edge, the fidelity of the edge is being compromised.

2.3.1(b) Iterative Blind Deconvolution

Iterative Blind Deconvolution is another class of blind deconvolution. It is a method that incorporates the blur identification procedure with the restoration algorithm into one procedure. This merge involves estimation for the PSF and the true image in iterative steps simultaneously, which leads to the development of more complex algorithms. One of the examples is the works from Sheppard *et al.(*1998). In their works, parametric models are formulated for both the image and the blur. This method required iterative procedure in which in each step the image and the blur parameters are estimated. They are then used in the next iteration. A Gaussian function is often used to approximate the atmospheric PSF. Many iterative blind deconvolution methods exist; two major methods are the **Richardson–Lucy (RL)** deconvolution (Conchello et al., 1996; Van Kempen et al., 2000) and **Expectation Maximization (EM)** (White, 1997; Bretschneider, 2002).

The RL deconvolution has many advantages over the classic linear methods, including the fact that it produces restored images that are non-negative, while conserving the intensity of the image during iteration. In addition, the restored images are robust against small errors in the PSF. However, this algorithm demands a manageable amount of computer time. The main drawback of this algorithm is that it may have a noise amplification problem. Traditionally, in order to overcome this difficulty, the usual approach is to stop the iteration when the restored image seems to be too noisy. According to some researchers, the issue of the sensitivity to noise can be avoided with the help of regularization constraints. Conchello *et al*.(1996) and Van Kempen *et al.*(2000) have presented a RL algorithm using energy-based regularization applied to biological images, leading to much improved results. In the problems where the point spread function is dependent on one or more unknown parameters, the Richardson–Lucy algorithm cannot be used. A later and more general class of algorithms, the EM (Dempster *et al.* 1977) has been applied to this type of problem with great success; Maximum Likelihood Estimation (MLE) is a type of EM algorithm (Shan *et al.*, 2008).

MLE techniques attempt to fit the data as closely as possible (Lagendijk *et al.*, 1990). If the degraded image is very noisy, trying to fit the noise too closely with much iteration may result in a restored image with speckled appearance. One possible solution to avoid this undesired effect is the integration of a damping factor that was usually used in image restoration (White, 1997). However, for the particular case of estimating the PSF, the utilization of constraints on the intermediate estimates within iterations leads to faster convergences. It allows a more flexible approach to include additional *a priori* knowledge about the imaging function (Bretschneider, 2002). Bretschneider (2002) suggests a modification of MLE that is similar to the idea depicted by Pruksch and Fleischmann (1998). In his works, he includes Gaussian statistics to overcome the noise amplification, this attempt results an improved result and analysis led to the assumption that the results of the MLE are more likely to describe the actual PSF compared to the classical Wiener Filter.

The main drawback of iterative blind deconvolution is that a good initial guess of the PSF is required to ensure the accuracy of the estimated PSF, which consequently affect the quality of the restored images. In order to overcome this problem, Loyev and Yitzhaky (2006) proposed a so-called *direct–iterative blind deconvolution* method by applying the pseudo whitening method (Yitzhaky *et al.* 1998) as a direct process to estimate the initial PSF. It later continues with Richardson–Lucy or Expectation Maximization as the iterative process to produce the final (refined) estimated PSF and restored image. The motivation of this work is based on the idea that the quality of the restored image is related directly to the quality of the final estimated PSF. Any improvement of estimated PSF will lead to a better image restoration. Therefore the iterative methods are likely to be improved when a more accurate initial PSF is used that can be estimated using direct method. The shortcoming of this method is the complexity of the algorithm.

Another drawback of *iterative blind deconvolution* filter is that it tends to suffer from unpleasant ringing artifacts that appear near strong edges. Shan *et al*. (2008) proposed to remove motion blur from a single image by minimizing errors caused by inaccurate blur kernel estimation and image noise. The main contribution is an effective model for image noise that accounts for its spatial distribution, and a local prior to suppress ringing artifacts. These two models interact with each other using Maximum Likelihood to improve unblurred image estimation, even with a very simple and inaccurate initial kernel, after advanced optimization process is applied. The drawback of this method is the compromise of a reasonable computational load.

Based on the literature review on solutions to image degradation problem, it is obvious that deconvolution in image restoration technique would be the most suitable technique for spatial image quality improvement, since it is an objective process for restoration and best formulated in frequency domain. Remotely sensed images usually undergo a lot of signal interference from imaging hardware component and environmental prior to its conversion to digital representation. So literally, it is more appropriate to work in the Fourier transform domain.