Compressive Sensing based Satellite Image Fusion

By

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DECLARATION OF AUTHENTICATION

I certify that the research work presented in this thesis is to the best of my knowledge my own. All sources used and any help received in the preparation of this dissertation have been acknowledged. I hereby declare that I have not submitted this material, either in whole or in part, for any other degree at this or any other institution.

Signature……………………..

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Last, but not the least I would like to thank my beloved parents for their continuous support, love and encouragement for the completion of this dissertation. I am also grateful to my friends for the concern, help and motivation regarding this research.

DEDICATION

This thesis is dedicated to my beloved parents and to all those who encouraged and supported me to achieve my goals.

ABSTRACT

Image fusion is the process of integrating the relevant information from two or more images into a single image. In traditional methods of pan sharpening, the fused images suffered from spectral distortion. In recent literature, filter based methods were proposed and they are often used as compared to other fusion methods because of their ability to improve spatial and spectral quality. In filter based techniques, spatial information from panchromatic image is injected into the multispectral image. A compressive sensing based filter approach is proposed in this research. Compressive sensing aims to construct the fewer samples from many signals by using only a few non-zero coefficients in a suitable basis. These few samples can efficiently represent the input signals. In proposed technique, regression coefficients are calculated from compressive signals of panchromatic and multispectral images. An optimized filter is constructed from regression coefficients and input images. Filter extracts the significant and non-redundant information from input images. Low resolution panchromatic image is then constructed from optimized filter and input panchromatic image. Finally, low resolution panchromatic image is injected into the multispectral image. Input images of different resolutions, sizes, backgrounds and locations were used in our experiments. Final fused images were evaluated using two spectral quality measurement techniques and four fusion quality assessment techniques. Visual and quantitative results show that the proposed algorithm produces better results in terms of spectral and fusion quality as compared to the previously presented methodologies.

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List of Abbreviations

MS	Multispectral
P	Panchromatic
CS	Compressive Sensing
IR	Infrared
CT	Computed Tomography
MRI	Magnetic Resonance Image
PCA	Principal Component Analysis
BT	Brovey Transform
DWT	Discrete Wavelet Transform
ERGAS	Relative Global-Dimensional Synthesis Error
CC	Correlation Coefficient

Introduction

Nowadays, we have multiple image sensors that work on different spectrums. Each sensor provides an image with a particular type of quality. The goal of image fusion is to integrate complementary multi-sensor, multi-temporal or multi-view information into one new image [1]. The quality of fused image relies on the fusion algorithm. The term quality, its meaning and measurement depend on the particular application. Each object of scenery can be better analyzed in a single image containing information of all input images. Image fusion is one better solution to merge the information of images [1].

Image fusion is performed with the aim to obtain new or more precise knowledge. It generates a result which describes the scene better than any single input image. Information sources used for fusion refer to common underlying events [1]. Image fusion seeks to combine the information of multiple input sources. The composite image is formed to improve image content and to make it easier for the user to detect, recognize, and identify targets and increase his situational awareness [2].

1.1 Image Fusion

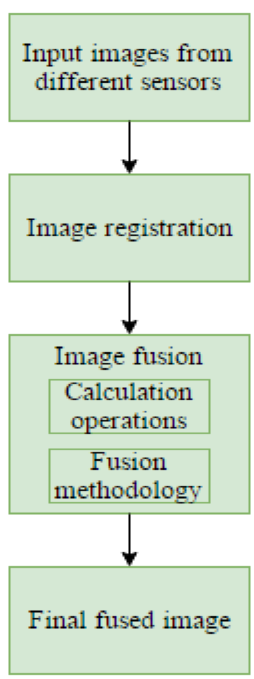

Figure 1.1: Image Fusion Process

Image fusion is the process of combining relevant information from two or more images into a single image. Image fusion helps to extend the range of operations in many fields and also increases spatial coverage [2]. Decisions based on fused image will have less uncertainty and more reliability [2]. Image fusion process is shown in Figure 1.1.

1.1.1 Input Image / Images

In image fusion, the raw images on which fusion process is applied are called the input images. These images are produced by different sensors at different spectrums [3]. Multiple input images can be used in fusion.

1.1.2 Image Registration

In this step, information of each input image is processed and transformed. Input images are prepared for the fusion process. In several fields, direct fusion on raw images suffers from different degradations [3]. Before applying fusion one or more input images are normalized according to other input image [3].

1.1.3 Image Fusion

Finally input images are fused to get a final fused image. Depending on the nature of fusion algorithm, different calculations are performed on input images. Each pixel of one input image is merged with respective pixel of other input image. In this step, a final result is calculated by combining the information of all input images [3]. This is the main step of image fusion [3].

1.1.4 Final Fused Image

By taking one or more input images, a single resultant image is produced as an output of image fusion process. This fused image contains the properties of all input images. Resolutions and dimensions of final image should be similar to input images [3]. Quality of fused image depends on image registration and image fusion steps. A good fused image will possess the features of all input images [3].

1.2 Fields of Image Fusion

Image fusion is a technique used for compact representation of information [4]. These are some areas where image fusion is essential part of many operations.

1.2.1 Visible IR

In this domain, visible image is fused with IR image. The information content for visible image is different than for IR image [4]. Reflectance of objects is different in light than the IR image [4]. Foliage is much more exhausted in IR than visible images [4]. Some objects become transparent in IR image and some become transparent in visible image. Visible image sensors more focus on color quality of the scenery and IR sensors more focus on objects. Image quality can be enhanced by fusion of visible and IR images. Visible and IR sensors are used in surveillance and remote sensing images where the interesting objects are needed to be highlighted [5]. In some cases IR images can be more dominant in image fusion to recognize the object while compromising on the natural colors of object [5]. In some other scenarios, image fusion focuses on color information such as in color night vision. These colored images of night vision are much better for understanding the spectral information than the IR images but these colors are not similar to the colors of same scenery at day time [4]. Image fusion helps to get a better guess about observed objects such as human beings in surveillance domain [4].

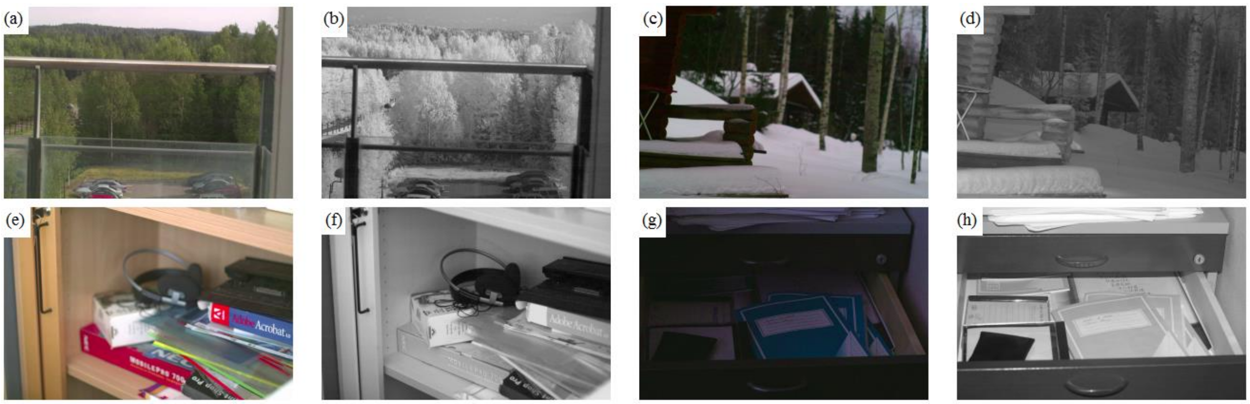

Figure 1.2: Visible IR Images (a) Visible in daylight (b) IR in daylight (c) Visible in evening (d) IR in evening (e) Visible in bulb light (f) IR in bulb light (g) Visible in dim light (f) IR in dim light [4]

In Figure 1.2 (a) there is a view of natural scenery and some automobiles [4]. Visible spectrum image clearly shows the colors of all objects. Difference between the colors of trees and grass can easily be observed. The colors of automobiles can be recognized. In Figure 1.2 (b) the street light globes are not much prominent in visible image than IR image. Hidden objects are much clear in IR image [4]. In Figure 1.2 (c) there is a view of house in a forest. Figure 1.2 (c) is providing much clear view and color information in this scene while Figure 1.2 (d), an IR image is degrading the color but it is clearly showing the each feature of all objects [4]. In Figure 1.2 (e) and Figure 1.2 (f), a headphone and some books are placed on the shelf. It is easier to observe the color difference and to recognize the objects in Figure 1.2 (e) due to the presence of enough light in this scene. In this case, Figure 1.2 (f) is not helping much in identification of objects. In Figure 1.2 (g), there is open draw with some books. In this image, the colors of objects can be identified. Some objects are clear where the light intensity is high while other objects placed in dark side of scenery can’t be seen clearly [4]. Figure 1.2 (h) is very useful to recognize the objects. Papers in low light are almost obscure in Figure 1.2 (g). Handles on draw can be clearly seen in Figure 1.2 (h). So, in some situations where light is high visible sensor delivers more information than IR while in low light circumstances IR provides more details than visible [4].

1.2.2 Medical Imaging

Image fusion plays an important role in medical field. In modern treatments, different sensors are used to get the better idea of internal parts of human body. These sensors provide different information about single organ of human body [6]. A medical person can better understand the disease or condition of an organ when information of all sensors is merged into a single image. It improves the efficacy of infection diagnosis which eventually leads to better cure suggestion [6]. In the field of radiology, Computed Tomography (CT) and Magnetic Resonance Image (MRI) are used. CT and MRI are merged to get all information in single fused image. CT images are more often used to ascertain differences between the tissue densities while MRI images are used to diagnose the brain tumors [7]. In angiography, Coronary Angiography is complex with Coronary Artery By-pass Grafts (CABG) where CT three dimensional (3D) models are fused with fluoroscopic images in real time to get the better understanding about effected areas [7].

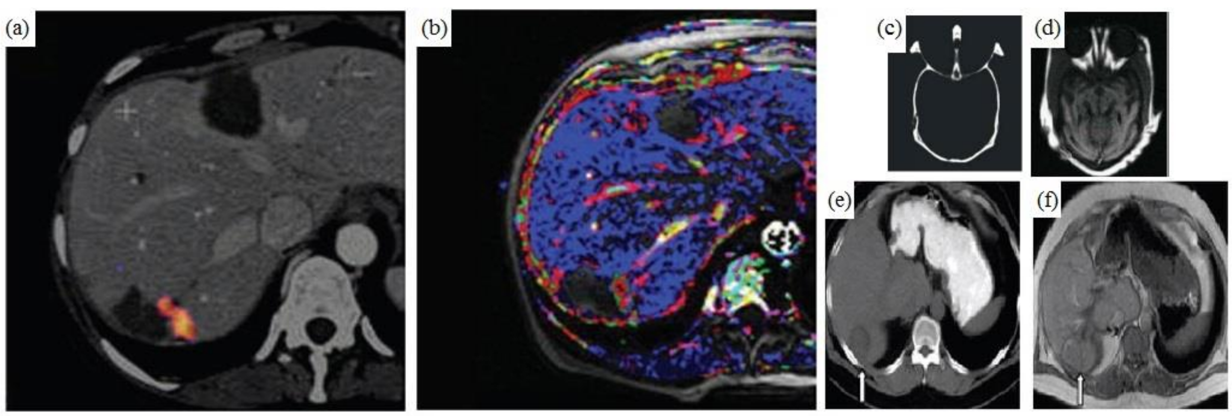

Figure 1.3: Medical Images (a) PET/CT (b) Dynamic contrast enhanced MRI (c) CT of Brain (d) MRI of Brain (e) Axial CT of Liver (f) Axial MRI of Liver [7, 8]

1.2.3 Multi-focus Images

It is difficult to get the all objects in focus with single camera due to finite depth of field (DOF) of optical lenses [9]. Usually those objects which appear in sharp DOF of lenses are appeared to be in focus while others are appeared blur [9]. Multiple sensors with different DOF are used to produce the images of objects at different distances. Some sensors focus on closer objects more properly and some focus on distant objects. All objects of scenery can't be focused with single lens of particular DOF [9]. Image fusion provides the solution to produce the single image that has all objects in focus. Fusion process picks the focused part of each input image and merges them to make the final fused image [9]. Fused image will be more understandable for machine or human perception. Objects can be recognized in the final fused image [9]. It also deals with the moving objects of scenery [9]. Furthermore, due to the different imaging parameters for multiple source images, the location of object edges in different source images cannot be exactly the same [9]. Multi-focus images are shown in Figure 1.4.

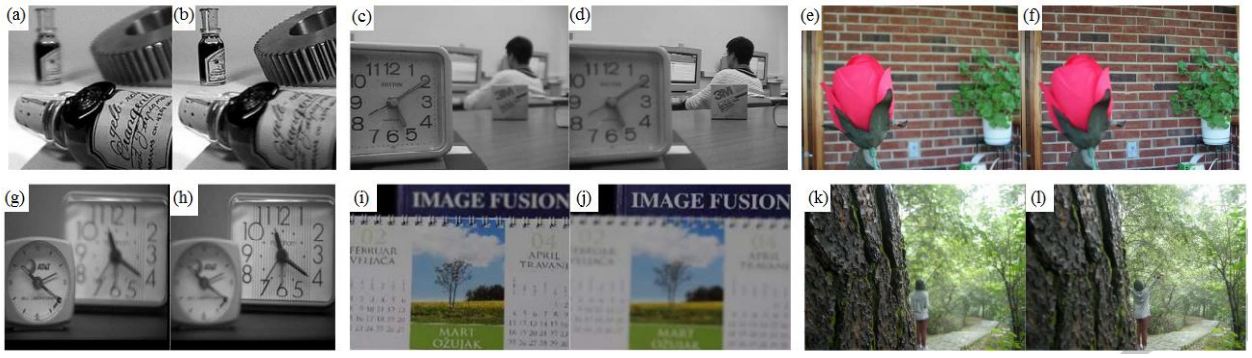

Figure 1.4: Multi-focus Images (a) Focus on near objects (b) Focus on distant objects (c) Clock is in focus (d) Person is in focus (e) Focus on flower (f) Focus on plant (g) Close clock is in focus (h) Distant clock is in focus (i) Lower part of calendar is in focus (j) Upper part of calendar is in focus (k) Focus tree (l) Focus on scenery and human [9]

1.2.4 Satellite Images

Satellite images are acquired from multiple sensors which have different resolution and spectrum [2]. Some satellite images are shown in Figure 1.5.

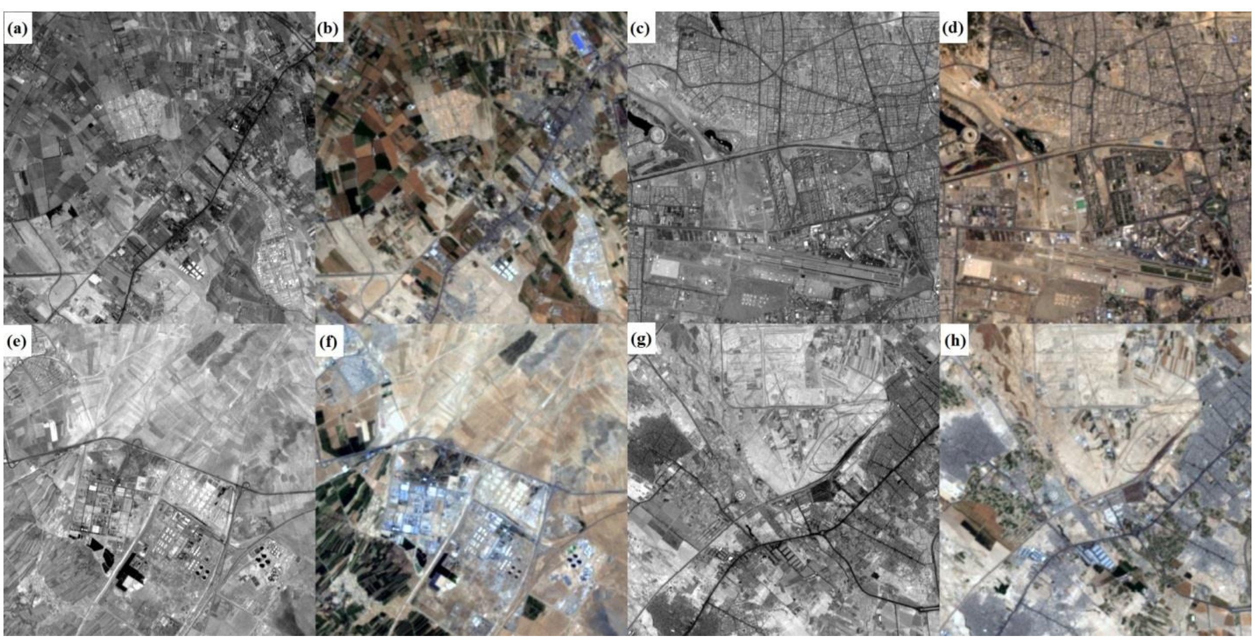

Figure 1.5: Satellite Images, IKNOS [(a) Panchromatic (b) Multispectral] LANDSAT [(c) Panchromatic (d) Multispectral] Quickbird [(e) Panchromatic (f) Multispectral] Quickbird [(g) Panchromatic (h) Multispectral] [10, 11]

Mainly two types of sensors are used in remote sensing, multispectral (MS) sensors with high spectral and low spatial resolution and panchromatic (P) sensors having high spatial and low spectral resolution [2]. Multispectral image has few spectral bands whereas panchromatic image is a single band image [2]. In image fusion, high spatial information is combined with suitable spectral information [2]. Final fused image contains the color information of multispectral image and spatial information of the panchromatic image [2].

1.3 Levels of Image Fusion

Image fusion can be performed on three different levels on the bases of image details. Nature of input images is the key factor for the selection of fusion level. Pixel level image fusion helps to preserve the minute details of each input image in the final fused image [12]. By preserving more details of input images, better fusion results can be easily achieved. Pixel level image fusion is widely used in remote sensing and medical imaging where more informative final fused images are required for better human or machine perception [12]. In some other techniques, such as multi-focus image fusion, feature level fusion is adopted where features are more important and algorithms can perform better fusion by judging the attributes of input images [12]. Feature level fusion helps to achieve the better results in human gesture analysis. In visual sensor network, multi-focus images are fused by using feature level fusion technique [1]. In some cases, details about images are extracted from different algorithms and then the decision of fusion is made on the bases of results provided by all algorithms [12]. Decision level image fusion is much suitable for detection of multiple objects in scenery [1]. Depending on the type of application, the appropriate image fusion approach is adopted [12].

Table 1.1 Comparisons of Image Fusion Levels [12]

Level Feature	Pixel Level	Feature Level	Decision Level
The amount of information	maximum	medium	minimum
Information loss	minimum	medium	maximum
Dependence of the sensor	maximum	medium	minimum
Immunity	the worst	medium	the best
Detection Performance	the best	medium	the worst

1.3.1 Pixel Level

This fusion is conducted on pixel by pixel basis. It generates the fused image which contains more information than input images [12]. In the field of remote sensing, fusion at this level leads to better spectral quality in the final fused image because it preserves the color information of pixels. It depends on the input images [12]. As shown in Table 1.1, the quality of final image suffers even if single input image is affected from distortion [12]. This level of fusion is in-depth fusion so it extracts maximum amount of information from input images so the loss of information is minimum. It has better performance due to good recognition of objects from a scene. This type of fusion depends on quality of sensor as shown in Table 1.1 [12].

1.3.2 Feature Level

Feature level image fusion is related to image features. It requires extraction of image features. Here the extracted features of all input images are combined to make a single fused image [4]. Pixel intensities or edges and texture are the features of images [4]. Different images have different type of features. Primary features are edges, regions, sharpness, size, length and segments of images [4]. Fusion at this level doesn't rely on detailed information of input images as shown in Table 1.1. It just gets the required features without getting in-depth details of input images and takes decision of fusion on those selected features of input images. It can detect some objects. As shown in Table 1.1, this level of fusion is not much dependent on input sensor [12].

1.3.3 Decision Level

It consists of higher level abstraction of information integration [12]. It deals with symbolic representation of the images. It combines the results of multiple algorithms to yield a final decision about the fusion process [4]. The main goal of this fusion is to use a set of independent classifiers to achieve higher robustness by combining the results of different algorithms [4]. It is performed by combining the decisions from the classifiers. It first employs feature extraction on the source data so that the features from each source can be jointly employed for some purpose [4]. Decision rules are applied on obtained information to make a final fused image [4]. This technique can't detect objects efficiently in a scene due to its higher level fusion as shown in Table 1.1. It is independent from the nature of input images because it relies on algorithms rather than input images [12].

1.4 Applications of Image Fusion

Image fusion has a broad range of applications where the fusion process is a critical part of many decision making policies [13]. Single image of definite spectrum and resolution can't provide enough information for better analysis of a scene. Analysis of a scene will be more efficient and decision on the bases of this analysis will be more precise when multiple types of information will be stored in one image [13]. In many fields, multiple sensors are used for single scene and here image fusion helps to merge all information in one image. When analyzers perform an analysis on different resolution images, each image provides them different information about every object of scenery [13]. This type of analysis will not give much information to draw a better conclusion. Investigation on single fused image will be much easier than multiple images [13]. These are some areas where fusion performs key role.

1.4.1 Intelligent Robotics

Different sensors are used to make artificially intelligent systems [13]. Movements of robots and applying force or torque are dependent on their view prospect. These systems rely on their input and in most of the cases camera is used as an input source [13]. A single image can't provide the better information for making any decision. In stereo cameras, results of lenses are fused to get the complete view of scene [13]. Intelligent viewing control systems use different input scenes and fuse them for getting better conclusion [13]. Target recognition systems also use image fusion [13].

1.4.2 Medical Imaging

In the field of medical science, multiple images are used for the treatment of a disease [13]. Sometimes information of more than one images is required such as in the field of radiology, Computed Tomography (CT) images are used to identify the tissue density while Magnetic Resonance Images (MRI) are used for brain tumor diagnosis [13]. Fusion of these two images will help the physicians to understand both type of information more efficiently in a single fused image. This technique is effectively in use for the treatment of cancer [13]. Fusion is also used in Computer Assisted Surgery where different sensors get images at different angles [13].

1.4.3 Manufacturing

Electronic circuits are inspected by using different images. Image fusion merges very minute details which are observed during construction of a circuit [13]. During assembly process, product features are inspected by using different sensors to analyze the product quality [13]. Complex devices are inspected through a fused image that contains properties of different images of different resolutions [13]. Fusion process is helpful in clearly examining the assembly line of robots. Depending on distance between lens and object, different sensors focus different parts of same scene. Fused image merges the focus parts of input images and contains the full strong information [13].

1.4.4 Military and Law Enforcement

Detection of earth and target is most important objective for military and law enforcement agencies [13]. Ocean, air, ground and sand are detected in different sensors and image fusion shows them all in single fused image. Different sensors track the target or event in different manners. Battle field monitoring can be easily performed by fusion of different images [13]. Pilot's guidance requires information of same scene with different resolutions, especially at night when one sensor adds extra brightness effect in scene and other gets the original scene [13]. Any camouflage weapons can be easily identified by merging different resolution scenes in a single image [13].

1.4.5 Remote Sensing

Multispectral and panchromatic are two main types of input images used in this fusion process [13]. Multispectral images have good spectral quality but compromise on spatial aspects of the scene while on the other end, panchromatic images have high spatial and low spectral resolution because of their different electro-magnetic spectrum. Colors are taken from one image and sharpness from the other, to make a perfect combination for final fused image. Panchromatic image is a single band gray-scale image. Multispectral is a multi-band image that can have three to many bands. It has three main bands RGB which contains the main color quality of an image [13].

1.5 Problem Statement

Develop an algorithm for multi-sensor satellite image fusion that produces comparable results to existing techniques in terms of spectral and spatial qualities but addresses the problem of computational complexity.

1.6 Proposed Methodology and Research Contribution

In this thesis, we have proposed an optimized filter based image fusion approach by using a low resolution panchromatic image. Optimized filter extracts the spatial information from panchromatic image and fuses it with spectral information of multispectral image. Injecting optimized spatial information in multispectral image leads to achieve better spectral quality and also better fusion quality. In this research, block based compressive sensing technique was adopted that helped to get fewer samples from input images. Image information is mapped onto compressive signals and used for calculation purpose. Low pass filter perform the calculations on CS values. Results calculated using fewer samples are comparable to the results obtained using large scale images.

1.7 Thesis Outline

This chapter provides an overview of the image fusion process and describes its applications in different fields. In chapter 2, a comparative analysis of existing techniques of image fusion and compressive sensing is discussed and specifically, the satellite image fusion techniques are described in detail. Modern filter based approach of image fusion is also described in chapter 2. In chapter 3, we explain the proposed methodology in detail and also discuss the achievements of proposed technique. In chapter 4, experimental results of proposed methodology are compared with existing techniques in terms of spectral and spatial qualities. Well known image fusion quality matrices are used to evaluate the spatial and spectral qualities of final fused images. A large number of experiments are performed in chapter 4. Chapter 5 discusses the future work directions in the field of satellite image fusion.

Literature Review

Image fusion produces the final image by merging two or more images. Final fused image will have more complete and more understandable information than any input image [14]. Information from each input image is combined in the final fused image. This type of image fusion is also called multi-sensor image fusion [14]. In recent few decades, many sensors have been invented to get different resolution images of scenery. A particular type of sensor provides specific information regarding a scene [14]. Information of each input image is merged in one image by using image fusion [14]. Different sensors work on different resolutions and spectrums so the quality of their image will be good in some aspects and suffer in others, such as in the field of remote sensing, some sensors provide images with better spectral resolution for example IKONOS, SPOT 4 and some provide images with better spatial resolution for example Landsat 8, SPOT 1 HRV [14]. A single sensor cannot provide the better spatial and spectral qualities at the same time [14]. A good image must possess a large variety of qualities so that the image can be used for multiple purposes [14]. In several situations, the qualities of all input images are needed to be analyzed in a single image. Here image fusion helps to merge the all qualities of input images and produces a single output image for better analysis. In recent years, image fusion has helped a lot in taking many critical decisions in the field of medical treatment and surveillance object recognition [14]. A good image fusion algorithm preserves the qualities of all input images in the fused image [14]. Many fusion algorithms were devised in recent years; some of them are comprehensively discussed in this chapter.

Compressive sensing (CS) helps to generate fewer samples from an image and reconstruct the same image from those samples [15]. In recent years, CS has procured a lot of attention as a substitute of compression because it does not compress the signals rather it sparse the signals [15]. Redundancy of signals is exploited by conducting the samples and reducing the signal quantity. CS produces samples of data independently from original signals. It is dependent on L1-Minimization technique, which has an important role in many scientific fields [15]. In the field of image processing, this technique helps to perform calculations on fewer samples which help to reduce the complexity of processing. By using this technique, input images can be reconstructed from very few samples than required by a famous Shannon-Nyquist sampling theorem [15]. CS depends on sparsity of signals rather than highest frequency [15]. This theory demonstrates that very few samples of signals can be used to get the complete information of signals [15]. In recent few years many algorithms of CS were proposed, some of them are explained in this chapter.

2.1 Important Factors in Image Fusion

Image fusion quality is evaluated from the fused image. Two aspects are very important in image fusion process. One is quality of sensors that produce the input images and other is algorithm which is used for the process of image fusion [16]. Different sensors are used to produce the images of same scene and each sensor works on specific resolution and specific spectrum [16]. A sensor must be eligible to produce an input image which possesses all the qualities for which the sensor was used. For example in the field of remote sensing, quality of panchromatic sensor depends on the spatial quality of its produced images. Quality of multispectral sensor can be judged through the spectral quality of its produced images. A fusion algorithm is more important factor in image fusion because the final fused image must preserve the qualities of its input images [16]. For example in the field of remote sensing, fusion algorithm must produce a fused image with good spatial and spectral qualities. In chapter 4, the quality of final fused image is evaluated in different aspects.

2.2 Satellite Image Fusion

It is an important domain in multi-resolution image fusion using panchromatic and multispectral images. Image fusion in this domain can have multiple input images but most of the times, fusion is performed on two input images [17]. Pixel based image fusion is used in satellite image fusion [17]. In image fusion process, single panchromatic image is fused with each band of the multispectral image to get the better fusion results [17]. In traditional techniques, single band of the multispectral image was selected and fused with the panchromatic image values or one band of the multispectral image is replaced with the panchromatic image [17]. So, the traditional techniques suffer from spectral distortion and deteriorate the fusion quality as well. Each band of satellite images is important to achieve good fusion quality. In the field of remote sensing, different pixel based algorithms are used for pan sharpening. Final fused image should contain the spatial and the spectral qualities of panchromatic and multispectral images, respectively. A good fusion algorithm produces the fused image with minimum spectral distortion [17]. In the field of remote sensing, high resolution panchromatic images with high spatial quality and low resolution multispectral images with high spectral quality are fused to produce the final fused images [17]. In fusion process, dominant panchromatic image hide some aspects of multispectral image which leads to spectral distortion. Average calculation of pixels does not provide better fusion results in satellite image fusion because features of multispectral image are suppressed due to its lower resolution than panchromatic image [17] and fused image suffers from spectral distortion. For better image fusion, either the resolution of multispectral image should increase at the level of the panchromatic image resolution or a low resolution panchromatic image should be constructed so that the fused image should not suffer from spectral distortion [17]. In modern techniques, panchromatic image is merged with all bands of the multispectral image to retain the spectral qualities of the multispectral image [17].

2.2.1 Panchromatic Sensing

A panchromatic image is obtained when sensor is corresponding to visible part of the scenery in Panchromatic mode (P) [18]. In this mode, sensor focuses on the center with narrow bandwidth [18]. It generates a high resolution output image. Single channel imaging mode is selected for sensors to generate a panchromatic image. It produces a black and white mono-spectral single band image with gray shades. Panchromatic image is acquired at extensive visual wavelength spanning over a large part of the visible spectrum [18]. It has sharp effect for every object of the image. Each element in the image can be easily differentiated from the other. Properties such as size, length and sharpness of each item in panchromatic image are clear as shown in Figure 2.1 (A). Panchromatic sensor requires a low level of light energy that is used to differentiate the objects in scenery [18]. High resolution panchromatic image is used in Figure 2.1 to analyze the better results of fusion process. Single band of panchromatic image is used to get the fine geometrical details [18]. SPOT 1, 2 HRV sensors are used in panchromatic sensing. A SPOT panchromatic sensor provides high resolution image data. It has 10 meter panchromatic picture resolution capability and covers 0.51 µm to 0.73 µm for its image [18].

2.2.2 Multispectral Sensing

Sensors perform imaging in three or more different spectral bands in multispectral mode (XS) [18]. In most of the cases, three spectral bands are covered. Multispectral image is generated in more than one wavelength intervals [18]. It possesses more than one band in single image. In visual prospective, combination of three bands represents a colored image while each band remains as a gray scale image [18]. Its produced image can possess the color of each object of the scenery. Particular color of each part of scenery can easily be observed with human eye as shown in Figure 2.1 (B). It incorporates some blur effect in image because it ignores the sharpness effect but preserves the size and length of each image as shown in Figure 2.1 (B). Multispectral image incorporates three bands in itself in which one represents red color effect, second characterizes green color effect and third one signifies blue color effect [18]. A LANDSAT TM multispectral sensor delivers low resolution of 30m pixel image data [18]. Low resolution image containing efficient color of each object of the scenery is used in satellite image fusion. Multiple sensors are used for multispectral sensing such as SPOT 1, 2 HRV [18]. It has 20 meter multispectral picture resolution capability. It covers 0.50 µm to 0.59 µm using XS1 band for green color. It covers 0.61 µm to 0.68 µm using XS2 band for red color. It ranges 0.79 µm to 0.89 µm using XS3 band for near infrared [18]. SPOT 4 sensors have an additional spectral band XS4 for short-wave infrared wrapping 1.53 µm to 1.75 µm [18].

Satellite image fusion with different fusion algorithms is shown in Figure 2.1. Image (A) is input panchromatic image and image (B) is input Landsat-5 multispectral image. IHS fusion method produces the image (C). In IHS fusion result, the spectral quality has distorted. So dominance of input panchromatic image increases sharpness in the fused image. Image (D) is a fused image produced by Brovey fusion method. This technique has contrast problem in the fused image and suffers from blur effect. Image (E) is constructed by using PCA fusion method and it also suffers from spectral distortion. Fused image produced using PCA method can never represent the true color effect of input multispectral image. Fusion preserving spectral quality method is used in creation of image (F). FPSQ method has produced image with much better spectral quality but it suffers from fusion quality.

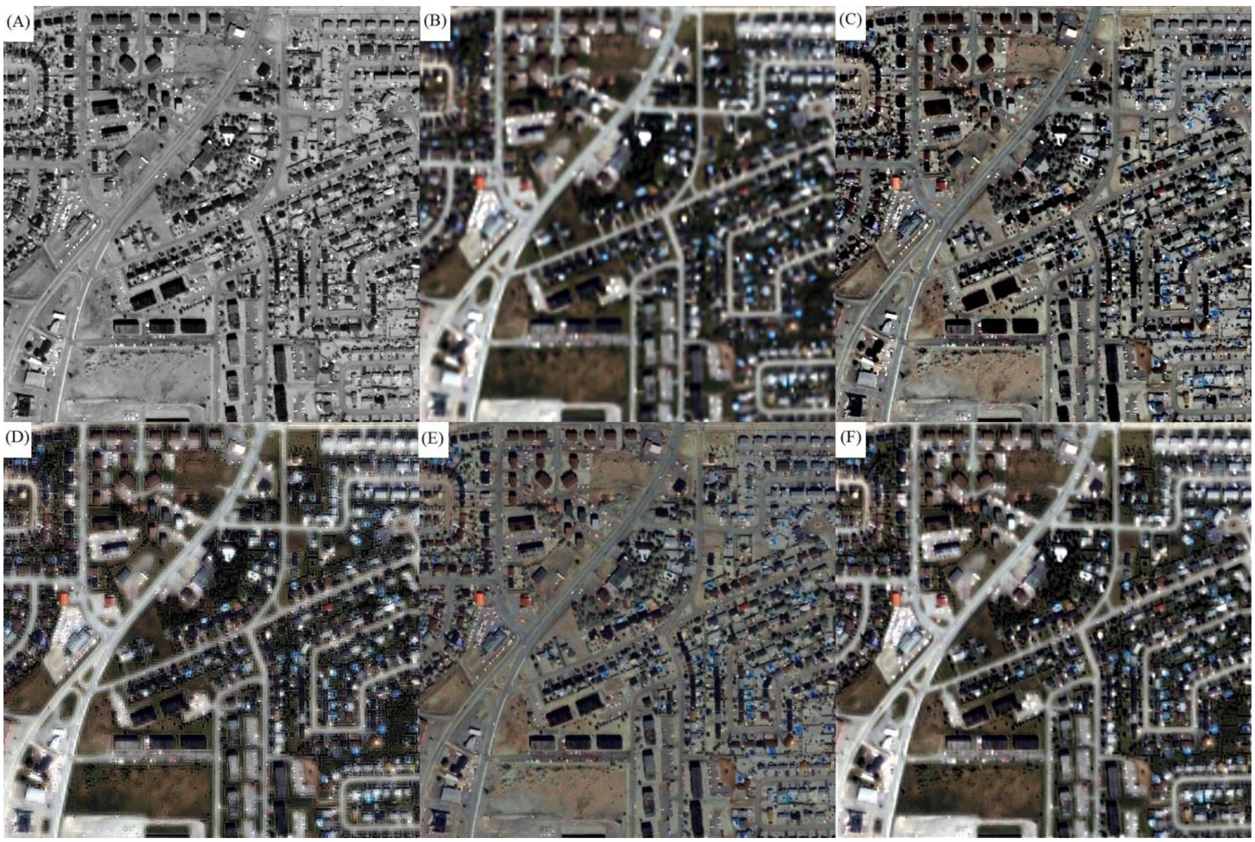

Figure 2.1: Different Fusion Algorithms [19]

Image fusion algorithms in satellite image fusion should focus on two things. One is to achieve the better fusion quality and other is to minimize the spectral distortion [2]. Both quality features should be in focus while designing a fusion technique. In the field of remote sensing, results of image fusion can't improve until fusion algorithm focuses to achieve the better spatial and spectral qualities [2]. All these fusion techniques either ignore the spectral quality or ignore the spatial quality in the final fused image. Final fused image should represent the each input image. Fusion quality in remote sensing is determined through spectral quality and spatial quality. Spectral quality is the similarity between the color scheme of the final fused image and the input multispectral image [2]. Spatial quality is the similarity between the final fused image and the input panchromatic image [2]. Fusion quality is used to determine that the final fused image is representing all the input images [2].

Fusion preserving spectral quality has much better spectral quality and better fusion quality as shown in Figure 2.1. But in case of very high resolution panchromatic image, it suffers with fusion quality while more focusing on spectral quality. Low pass filter is not much optimized in this technique.

2.3 Image Fusion Methods

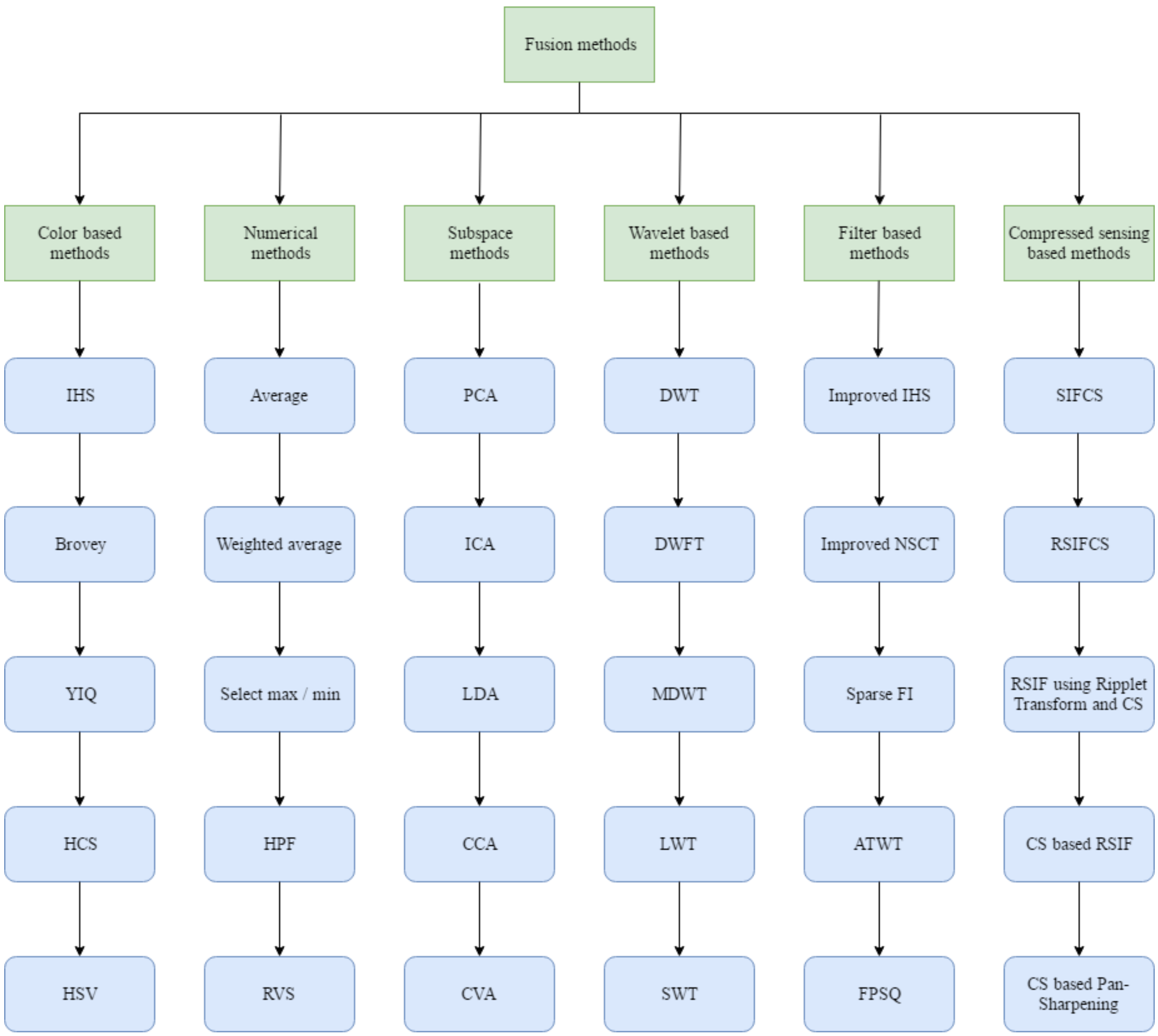

Figure 2.2: Image Fusion Methods

Image fusion can be performed with multiple fusion methods. Generally these methods are divided into six major categories depending on the nature of feature selection from input images.

Some methods more focus on the spectral details and some on the spatial details. Some methods deal with images at band level, some other methods deal with each pixel of the input images by using arithmetic calculations and some other methods deal with images on the basis of mathematical theory for producing better results of image fusion [20]. In this part, the image fusion techniques are explained in component substitution domain, filter based domain and compressive sensing domain. Component substitution algorithms focus on the spatial qualities and suffer from the spectral quality [2]. Component substitution domain is divided into spatial domain and transform domain. In spatial domain techniques, spatial quality remains in focus and one band of the spectral image is replaced or merged with the information of the spatial image [2]. In these techniques, the spatial quality remains preserved in the final fused image [2]. In this case, except one band, all bands of the spectral image become part of the fused image [2]. In transform based image fusion, all the bands of the input images are transformed into another domain. In this new domain, one band of the spectral image is replaced by the spatial image band [20]. In filter based techniques, a filter is created to generate the low resolution panchromatic image. Filter based methods have overcome the spectral distortion and preserved more spatial and spectral qualities in the final fused image as compared to the component substitution techniques [2]. These methods focus on the spectral quality of the fused image [2]. In compressive sensing based techniques, compressive signals are generated and fusion is either performed on compressive sensing signals or compressive sensing signals are used for multiple calculations in image fusion [15]. In past, many algorithms have been proposed for image fusion; some of them are discussed in this chapter.

2.3.1 Color Based Methods

Input images are treated according to their bands in this technique. Each band of the input image is transformed into another domain for the trade of fusion of the panchromatic image with all bands of the multispectral image [20]. Basic idea behind this methodology is to take in account the all bands of the multispectral image [20].

IHS (Intensity Hue Saturation) is one of the most commonly used image fusion technique [20]. It is a color enhancement technique. It transforms the RGB (Red, Green, Blue) bands of color image into IHS (Intensity, Hue, Saturation) domain [20]. It increases the resolution of the multispectral image and makes it equal to the resolution of the panchromatic image. Histogram matching is used to change the panchromatic image with respect to the multispectral image [20]. The intensity component I is replaced with the band of the panchromatic image [20]. It reverses the transform domain to get the high resolution final fused image [20].

RGB – IHS conversion [20]

$$I = R+G+B / 3$$ [20]

It focuses on feature enrichment in fused image and efficiently improves the spatial quality of the final fused image [20]. Spectral quality of the image is imitated on the hue and the saturation [20]. It is much better in terms of the spatial quality because all properties of the panchromatic image remains preserve in the final fused image [20]. Intensity hue saturation (IHS) is one of the popular pan-sharpening methods but it suffers from spectral distortion and also has less fusion quality.

In IHS fusion process, the low resolution multispectral image is transformed into a new domain for the fusion with the panchromatic image [21]. The R, G, B components of the multispectral image are transformed into IHS (Intensity Hue Saturation) domain [21]. Panchromatic image is reformed with respect to the multispectral image. Histogram matching process is implemented through matching the panchromatic image with intensity component of the multispectral image [21]. Intensity component is replaced by the panchromatic values and obtained inverse transform to produce the high resolution final fused image [21]. Spectral component is replaced with spatial values of the panchromatic image that leads to the spectral distortion which is evidently can be seen in Figure 2.1 (C). Spectral quality in IHS fused image is completely distorted. Fused image colors are not well matched with the multispectral input image. Colors are either light or completely disappear in the IHS fused image but spatial quality is much better than Brovey. Every object is clear in the fused image but shades and colors are not well accurate as compared to the multispectral input image as shown in Figure 2.1. In the final fused image, the sharpness at the points between two objects is increased in IHS.

Al-Wassai et al. presented an IHS based satellite image fusion methodology [20]. In presented technique, the low resolution multispectral image and the high resolution panchromatic image of same area are used [20]. Resolution of multispectral image is changed to the level of panchromatic image resolution. The three resampled RGB bands of the multispectral image are transformed into IHS components domain [20]. The panchromatic image is histogram matched to the component ‘I’ [20]. This is done in order to compensate the spectral differences [20]. The intensity component of the multispectral image is replaced by the histogram matched panchromatic image [20]. The RGB of the new merged multispectral image is obtained by computing a reverse IHS to RGB transforms [20].

Yonghyun, et al. used the spectral response functions of the satellite sensor; thus, it realistically reproduces the physical characteristics of the satellite sensor to the fused image [22]. Firstly, the low resolution multispectral images are resized to the high resolution panchromatic image scale [22]. The IHS method linearly transforms the RGB domain images into a more uncorrelated vector space [22]. Then, the intensity component is substituted by the high resolution panchromatic image before applying the inverse transform [22].

Brovey is RGB color transformation method [23]. It is the combination of color transformation and arithmetic operations. It normalizes the spectral quality of the multispectral input image before its fusion with the panchromatic input image [23]. It holds the spectral information of the pixels of multispectral image and merges the luminance information with a panchromatic image of high spatial quality [23]. Transformation is performed through a very simple formula [23].

$$Red = (Band\ 1 / \Sigma\ Band\ n) * P \text{ [23]}$$

$$Green = (Band\ 2 / \Sigma\ Band\ n) * P \text{ [23]}$$

$$Blue = (Band\ 3 / \Sigma\ Band\ n) * P \text{ [23]}$$

where n is total number of bands in the multispectral image and P is panchromatic image [23].

Brovey image fusion result shows that it emphasizes on the spectral quality of the fused image but it suffers from spectral quality due to wrong selection criteria for image fusion [23]. It is also called color normalization transformation method [23]. It was established and promoted by an American scientist Brovey [23]. It adopts the RGB color transformation strategy [24]. It normalizes the spectral bands of the multispectral image with respect to the panchromatic image using the arithmetic logic [23]. It transforms all the luminance information into a panchromatic image of high resolution [23]. Contrast is affected in the final fused image because it loses some information of the multispectral input image and fuses that information into the spatial information of the panchromatic input image [23]. In Brovey image fusion, difference of the contrast between the fused image and the multispectral input image is shown in Figure 2.2. It also suffers from the blur effect and objects are not enough clear for visual understanding.

BT (Brovey Transform) is a three bands transformation fusion technique [24]. It can’t handle the spectral images with more than three bands [24]. In case of long temporal changes in the spectral image, spectral quality distortion can be easily observed in the fused image [25]. Depth of each pixel cannot easily measure in this technique [24]. Brovey uses the mathematical combination of the high resolution spatial image and the low resolution spectral image. It calculates the value for each band of the final fused image by multiplying high resolution panchromatic image with low resolution multispectral image and divided by the sum of all bands [25]. BT retains the spectral quality of the multispectral image to some extent [25]. It provides better spectral results as compared to the wavelet based methods [25]. It handles the fusion fluctuations in pretreatment of input images. It retains the spectral quality of input multispectral image as compared to IHS [26] as shown in Figure 2.1 (D). Brovey has comparable fusion quality but it suffers from spectral distortion [26].

Gharbia et al. proposed a technique based on a modified version of Brovey transform and wavelets [24]. The aim of this technique is to reduce the spectral distortion in the Brovey transform and spatial distortion in the wavelets transform. In proposed technique, the Brovey transform is applied on the multispectral images and produce new images in RGB domain [24]. High resolution panchromatic image is decomposed into a set of low resolution values by using the wavelet transform [24]. The wavelet transform with the same decomposition scale is applied to obtain the wavelet coefficients for the new image (Rnew, Gnew and Bnew) [24]. This technique replaces low frequency of the panchromatic image with low frequency of the multispectral band at the same level [24].

Zhao et al. used the Brovey image fusion technique [25]. In proposed technique, the high spatial resolution panchromatic images are merged with the high spectral resolution multispectral images to produce the final image in RGB domain by using Brovey [25]. In this technique, WorldView-3 (WV-3) imagery was investigated for generating pan-sharped multispectral images [25].

YIQ is a color space in which I stands for in-phase and Q stands for quadrature [27]. RGB is not a good form of color domain for image fusion so original domain is transformed into another domain to attain the better fusion results. In this model, Y represents luminance component, I and Q symbolize the chromatic information [27]. Transformation of RGB into YIQ follows a model. This transformation provides the better color information in the fused image. In this technique, domain is transformed through this equation [27].

$$Y = 0.299R + 0.587G + 0.144B \text{ [27]}$$

$$I = 0.569R - 0.275G - 0.321B \text{ [27]}$$

$$Q = 0.212R - 0.523G + 0.311B \text{ [27]}$$

HCS (Hyper-spherical Color Space) is very similar to IHS color space. It has single intensity component which is separated from the n-dimensional hyper-spherical space [28]. This technique can fuse the n-band multispectral image with the panchromatic image [28]. For an n-band image, n-dimensional hyper-spherical color space forms an intensity (I) component. It produces the fused image with good spatial quality as compared to IHS [29]. It has improved the spectral quality in the fused image as compared to other color based image fusion methods [29].

S. Yang et al. proposed a pan-sharpening technique using HCS [28]. In this technique, fusion of high resolution remote sensing images is based on the second generation curvelet transform and the hyper-spherical color space transform [28]. This technique can fuse the panchromatic and the n-band multispectral images [28]. Results are quantitatively analyzed through multiple techniques. This technique has improved the spatial and spectral quality of the fused image [28].

A new satellite image fusion technique based on HCS is proposed [29]. In proposed technique, HCS fusion method is improved by combining the wavelet transformation and the spectrum gain modulation [29]. This technique mainly contains three steps [29]. (1) Angular component from the multispectral images is extracted through hyper-spherical color transformation (HCT). (2) A moderated multispectral image is produced by using the spectrum gain modulation. (3) By using multi-scale wavelet decomposition, the spectral details of the multispectral image are fused with the spatial details of the panchromatic image [29].

HSV (Hue Saturation Value) is very similar to IHS [30]. RGB bands of the multispectral image are transformed into HSV components [30]. Value component of the multispectral image is replaced by the panchromatic image and inverse transform is applied to produce the high spatial resolution multispectral image [30]. It is one of the widely used pan-sharpening methods for the three band multispectral images [30]. RGB is converted to HSV by following equation [30].

$$\begin{bmatrix} V \\ V_1 \\ V_2 \end{bmatrix} = \begin{bmatrix} 0.577 & 0.577 & 0.577 \\ -0.408 & -0.408 & 0.816 \\ -0.707 & 0.707 & 1.703 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad [30]$$

In above equation, V, V1 and V3 are HSV values respectively for RGB bands [30].

Mandhare et al. proposed HSV pan-sharpening technique which is one of the most commonly used image fusion technique [30]. RGB image is transformed into HSV space by using a transformation methodology [30]. In this technique, green band of the multispectral image is enhanced and HSV method is applied on the enhanced multispectral image to produce the better spectral results [30].

Advantages

These are very simple and fast methods for image fusion [31]. These methods can merge the data of different sensors. They produce high resolution and superior spatial final fused images [31]. These methods show better visual interpretation in the final fused image [31].

Disadvantages

These methods ignore the spectral information [31]. This type of methods produce spectral distortion while more focusing on the spatial quality [31]. In remote sensing, the final fused image cannot represent the true colors of the multispectral image by using these methods.

2.3.2 Numerical Methods

These are well documented image fusion methods in which pixel by pixel value of the input images is used for fusion [32]. Final fused image is produced by using a mathematical formula.

Multispectral image is treated as a single entity in the process of fusion [32]. Each band of the multispectral image is merged with single band of the panchromatic image [32].

Average method is a simple average calculation image fusion technique [32]. Final fused image is calculated by taking the average intensity of each pixel of the input images [32]. Average is calculated for each pixel of one image with the corresponding pixel of other image [32].

$$F\ (i, j) = A\ (i, j) + B\ (i, j) / 2 \text{ [32]}$$

where F represents the final fused image, A is first input image, B is second input image, i and j are number of pixels [32]

In satellite image fusion, average calculation leads to spectral distortion in the fused image [32]. Properties of the multispectral image are ignored to some extend due to high resolution of panchromatic image. In the field of remote sensing, true representation of the input images is not possible by performing average calculation [32].

In weighted average technique, a worth is assigned to each input image. In fusion, average calculation is performed on the weights of input images [32]. High resolution input images are assigned with low weights and low resolution input images are assigned with high weights. Drawbacks of simple average have been overcome by weighted average technique [32].

$$F\ (i, j) = A\ (i_{\ (w)}, j_{\ (w)}) + B\ (i_{\ (w)}, j_{\ (w)}) / 2 \text{ [32]}$$

where F is the final fused image, A and B are input images, i (w) and j(w) are weights of i and j pixels [32].

If one image is more dominant in scene and has more luminance, low weight is assigned to this image as compared to the other input image [32]. Both images should be balanced after assigning the weights and then average is calculated on the pixel weight of one input image with corresponding pixel weight of the other input image [32]. But this technique leads to spectral distortion due to its simplicity [32].

In select max/min, maximum or minimum intensity of each pixel is selected correspondingly to produce the final fused image. Simple maximum or simple minimum is defined below [33].

$$F\ (i, j) = \Sigma_{\ i=1}^{N} \Sigma_{\ j=1}^{N} \max A\ (i, j)\ B\ (i, j) \text{ [33]}$$

$$F\ (i, j) = \Sigma_{\ i=1}^{N} \Sigma_{\ j=1}^{N} \min A\ (i, j)\ B\ (i, j) \text{ [33]}$$

where F is the final fused image, max and min are the functions for information selection, image A and B are input images. i and j represent the number of pixels [33].

HPF (High Pass Filter) model was first proposed by Schowengerdt [34]. This method reduces the data quantity for the fusion and produces the better spatial results for the Land-sat multispectral images [34]. This method efficiently reduces the lower frequency spectral information of the high resolution spatial image and fuse high resolution spatial information with the low resolution multispectral image [34]. It is a very simple method of image fusion.

$$HPF_{i,j,k} = (MS_{i,j,k} + FP_{i,j}) / 2 \quad [34]$$

In above equation, HPF is the fused image, MS is multispectral input image, FP represents to filtered result of the high pass filter and i and j are the pixels of k band. In this technique, multispectral data is incorporated with the spatial details of the panchromatic image [34].

RVS (Regression Variable Substitution) is an inter-band relation image fusion technique [35]. In this technique, channel of an image is replaced with the channel of another image by regression procedure in which replacement vector of the image is determined by linear combination [35]. This statistical based method simply replaces the one band of the multispectral image with the panchromatic image [35]. This technique produces the significantly promising results for image fusion in terms of spatial quality [35]. Each band of the multispectral image is merged with the single band of the panchromatic image [35]. This fusion technique can be expressed as following equation [35].

$$F_k = a_k + b_k \,.\, P \quad [35]$$

In above equation, F is the final fused image, a is bias parameter, b is scaling parameter, P represents panchromatic image and k is the number of bands of multispectral image. a_k and b_k are evaluated by following equations [35].

$$b_k = \frac{s_{PM\,k}}{s_{PP}} \quad [35]$$

where b_k is scaling parameter for band k, s_{PMk} is the covariance between the band k of the multispectral image and the panchromatic image and s_{PP} is the variance of the panchromatic image [35].

$$a_k = mean(M_k) - b_k \,.\, mean(P) \quad [35]$$

where a_k is bias parameter for band k, M_k is k band multispectral image and P is panchromatic image [35].

Advantages

These are very simple image fusion methods. These types of methods are easily understandable for implementation because a lot of mathematics is involved in them [31]. They perform better in merging the images taken from same type of sensors [31].

Disadvantages

Fused images of these methods have less contrast [31]. Noise can easily affect the final fused images [31]. Spectral quality of the fused image is distorted by using these methods in satellite image fusion.

2.3.3 Subspace Methods

These algorithms improve the spatial quality of the fused image by replacing specific component of the multispectral image with the panchromatic image [36].

PCA (Principal Component Analysis) is a simplest true eigenvector based multivariate analysis [36]. It increases the resolution of the multispectral input image to synchronize it with the panchromatic input image [36]. It combines the multiband image information into a single image with maximum amount of information [36]. Each band of the multispectral image is treated as a separate component because it transforms the correlated variable (each band) to uncorrelated variable (component) [37]. Panchromatic image histogram is matched with single component of the multispectral image in new domain [37]. Spectral quality of the multispectral input image is compromised to get the better spatial quality in the fused image [37]. First component of the multispectral image is replaced with the histogram matched panchromatic image. Inverse of PCA is computed to get the final fused image [37]. It also degrades the spectral quality because of complete component replacement [37]. In fusion process, PCA transformation is aligned with consistent gray scale mean and variance. Eigen values are averaged with the values of each pixel of the input images to get the normalized values for the final fused image [36]. Specific selection of values leads to the spectral distortion as shown in Figure 2.2. It lighters the colors of the fused image and changes the sharpness of the fused image. It less sharpens the image and less distorted as compared to IHS because of its normalized final values [36]. Spectral distortion in the fused image of this type of fusion can be easily observed in Figure 2.2. It has less blur effect as compared to IHS and Brovey. Principal component analysis (PCA) suffers from spectral distortion and has less fusion quality as well [37].

Sen et al. have proposed a new adaptive fusion methodology [38]. This technique is based on a window technique and modified form of the principle component analysis (PCA) technique [38].

Metwalli et al. presented an integrated method for the satellite image fusion [39]. In proposed technique, the PCA method and the HPF method are integrated to provide a pan sharpened multispectral image with superior spatial resolution and less spectral distortion [39].

ICA (Independent Component Analysis) improves the input images by using the same component approach but it minimizes the dependencies of fusion on the input images [40]. It generates the better components for all three bands of the multispectral input image [40]. Histogram of panchromatic image is generated with the help of independent component and an optimal histogram is replaced with the first component of the multispectral image [40]. It leads to less spectral distortion but the final fused image can't represent the true colors of the multispectral input image [40].

Ejaily et al. proposed an image fusion method to merge the panchromatic and the multispectral remote sensing satellite images using genetic algorithm to maximize the non-gaussianity of the independent components of ICA [41]. The genetic algorithm evolves the mixing matrix of the independent components of the multispectral image by maximizing the sharpness [41].

Ghahremani et al. presented a novel image fusion method based on combining the curvelet transform and independent component analysis (ICA) [42]. The idea is to map the multispectral bands onto a statistically independent domain to determine the intensity component, which contains the common information of the multispectral bands, and then pan-sharpen it using curvelets and a modified adaptive fusion rule [42].

LDA (Linear Discriminant Analysis) is a dimensionality reduction eigenvector based image fusion process [3]. It reduces the dimensions for all three bands of the multispectral input image [3]. It extracts the features of the multispectral image for its first band and the first component of the multispectral image is simply replaced by the histogram matched panchromatic image [3]. It works in the same way as PCA does but it reduces the number of calculations.

Hazim et al. presented new algorithm to fuse the multi-image in four steps [3]. First is discrete wavelet transform (DWT) for time to frequency conversion, second is feature extraction, third is feature selection based on LDA and finally classifies the feature level fusion [3]. In satellite images, the major constraints are the environmental changes that leads to the distortion in the images [3]. Communication between the satellite and the earth station suffers from the less bandwidth which cause the image distortion [3]. Image fusion provides the solution to overcome this drawback and produces the fused image with high spectral and spatial qualities [3]. In this technique, the information of the panchromatic image and the information of the multispectral or hyper-spectral image is integrated to produce the fused image with high spectral and high spatial qualities [3].

OCA (Oriented Component Analysis) is similar to linear statistical technique [44]. In image fusion, some signals increase the fusion quality and others decrease the fusion quality [44]. The aim of this technique is to maximize the response of the wanted signals and minimize the response of the unwanted signals [44]. In this technique, image fusion quality is improved by removing the redundant signals. It increases the signal to noise ratio to achieve the better fusion results as compared to PCA [44].

CVA (Change Vector Analysis) is used for analysis of change in a variable [45]. It is similar to PCA but it reduces the redundancy of the signals. In image fusion, redundant signals of the input images are decreased and non-redundant signals are used for the fusion [45]. Magnitude and direction of the spectral quality remains consistent by using this technique [45]. Different bands of the input images are changed into new domain and fusion is performed on new domain vectors. Greenery and brightness of the scene can efficiently improve by using the CVA [45].

Advantages

These are simple methods but provide high spatial quality [31]. These methods are famous because these methods prevent the feature dominance in the fused image [31].

Disadvantages

These methods suffer from spectral degradation [31]. By using these methods, high distortion is produced in the spectral attributes [31]. These methods lost the complete color scheme of the multispectral image in the fused image [31].

2.3.4 Wavelet Based Methods

Wavelet based methods are transformation of Fourier theory and works better in both time and space [46]. These are powerful mathematical techniques. These techniques are originally developed for signal processing but also applied in image fusion [31].

DWT (Discrete Wavelet Transform) is a domain in which signals are decomposed into a new form where each level represents single band [46]. It is a multi-resolution transformation technique which deals with each pixel of the input images [46]. Discontinuous signals are well detected by using this technique [46]. Image signals can easily be transformed into DWT domain. Image information can be well preserved in the fused image by using different kinds of decomposition coefficients [46]. Coefficients coming from different images can be easily combined to obtain the approximate coefficient [46]. After merging the information, inverse DWT is performed on the coefficients to get the final fused image. It can easily preserve the qualities of all input images [31]. DWT results are more accurate and convenient in the field of remote sensing. Image frequency domain analysis is performed in this fusion technique [46]. Image frequency separation is implemented in this technique [46]. In this methodology, difference between the low frequency bands is small and difference between high frequency bands is large for the same scenery. It follows wavelet substitution technique in which details of the multispectral image are substituted with the details of the panchromatic image in satellite image fusion [46]. Content of the panchromatic image is added into the multispectral image [46].

In medical field, color information can be preserved with other information by using DWT. It transforms two dimensional (2D) gray-scale image signals into multiple dimensions for multi-resolution analysis [47]. In this technique, low frequency information can be easily decreased in the scenarios where high frequency information is needed [47]. Filtering operations of DWT can transform the detail information of an image into wavelet form. It analyzes the image information at different frequencies by decomposing the image into detailed coefficients and coarse approximation [48]. Each input image is transformed into two levels. Each level has two coefficient sets, detail (HL, LH, HH) and approximation (LL) [48].

DWFT (Discrete Wavelet Frame Transform) is a technique in which the low resolution multispectral image is registered onto the high resolution panchromatic image [49]. Multispectral image is resampled to the level of the panchromatic image. Panchromatic histogram is created using the same technique as the IHS used [49]. Multispectral image is divided into frames and corresponding frame of the panchromatic image is fused with each frame of the multispectral image [49].

MDWT (M-band Discrete Wavelet Transform) is a technique used for M number of bands [49]. As previously described, most of the wavelet based techniques handle the three bands of the multispectral image in fusion but in this technique, more than three bands can be handled using the fusion process [49]. It is similar to the DWT [49]. These techniques do not preserve the spatial quality of panchromatic image in the final fused image [49].

LWT (Lifting Wavelet Transform) is a multi-resolution image fusion technique [50]. It is used for the construction of second generation wavelet [50]. It is an efficient technique based on the discrete wavelet transform. It is a three step technique [50]. In first step, source signals are divided into two subsets. In second step, odd coefficients are predicted based on neighboring even coefficients by using predictor. Details are generated from the prediction function. In last step, the scaling function coefficients are computed using the wavelet coefficients. Scaling function is applied on the predictor to produce the detailed coefficients [50]. Low resolution image is merged with the high resolution image by using this second generation image fusion technique [51].

SWT (Stationary Wavelet Transform) is a simple algorithm and very similar to the DWT method [52]. It is a multi-scale image fusion method [52]. It is not a time variant technique. It suppresses the down-sampling step to achieve the better fusion results [52]. In this technique, filters are up-sampled by inserting the zeros between the filter coefficients [52].

Advantages

Separation of the fine details in a signal can be easily performed by using these methods [53]. These methods can decompose the signals of input images and produce the fused image from those signals [53]. These techniques minimize the spectral distortion [31].

Disadvantages

It is difficult to handle the changes in base function for these methods [31]. The fused image has less spatial resolution. These methods are computationally slow [53]. Fusion quality is sacrificed in these methods [53].

2.3.5 Filter Based Methods

In recent few years, filter based image fusion techniques have been discussed in research. These techniques focus on spectral quality of the fused image [2]. In these techniques, the spectral distortion has been decreased vigilantly and the fusion process provides an image with good spectral quality and spatial quality [11]. Filter based approaches focus on decreasing the resolution of the panchromatic image so that this low resolution panchromatic image can be fused with each band of the multispectral image [11]. These pan sharpening techniques proposed a specific filter for fusion [2]. Image fusion quality can be improved by estimating the nature of input images [39]. Some latest image fusion techniques are shown in Table 2.1.

2.3.5.1 Filter Based Model

This model of image fusion constructs a low pass filter for the panchromatic input images [2]. Filter extracts the high frequency components of the panchromatic images. Extracted information of the panchromatic input image is injected into each band of the multispectral input image [2].

$$F_i = MS_i + G_i\,(P - h*P) \text{ [2]}$$

In above equation, F_i is the $_i$th band fused image, MS_i is the $_i$th band multispectral input image, P is the low resolution constructed panchromatic image and h is low pass filter and G_i represents the $_i$th band value of the regression coefficient between the panchromatic image and the multispectral image [2].

Value of G for every band of the multispectral image is determined from the regression between the multispectral band and the panchromatic image [2]. Formula of G is given below.

$$G_i = Cov\,(MS_i\,,\,P_L)\,/\,Var\,(P_L) \text{ [2]}$$

where G_i is the regression value for $_i$th band of the multispectral image. Cov represents covariance; MS_i is the $_i$th band multispectral image. P_L is the low resolution panchromatic image. Var represents variance [2].

2.3.5.2 Filter Based Satellite Image Fusion

In filter based techniques, optimized filter leads to optimal fusion results [54]. A moderate value of the low resolution panchromatic image will lead to a better fusion [54]. In this technique, the final fused image preserves the spatial and the spectral qualities with minimum spectral distortion [2]. Some filter based techniques are shown in Table 2.1.

Table 2.1 Filter Based Satellite Image Fusion Techniques [2, 39, 54, and 55, 56]

Technique	Year	Results	Complexity
Improved IHS [39]	2010	Details have been well protected in this technique but colors in local and global areas are altered.	Requires high spatial and spectral quality input images.
Improved NSCT [54]	2011	Spectral quality has been maintained in this method but disturbs geometry of image.	Fusion process is very slow due to large number of calculations.
Sparse FI [55]	2013	It preserves the spectral quality and spatial content but suffers from color distortion in some areas.	More time is required in fusion due to iterative nature.
ATWT [56]	2011	Spectral angle is well preserved but spatial information is degraded to some extent.	It has large number of calculations in image fusion.
FPSQ [2]	2015	Image features are well enhanced in terms of spectral quality but suffers from spatial and spectral quality in some parts of image.	Devised filter is not well optimized for producing the low resolution panchromatic image for fusion.

Filter based techniques are much better than the traditional image fusion techniques in terms of spatial and spectral qualities [39]. In satellite image fusion, mainly two types of sensors are used. Spatial sensors deliver high resolution images as compared to the spectral sensors [39]. This point indicates that either the spectral quality of the multispectral image should increase or the spatial quality of the panchromatic images should decrease to maintain the both qualities simultaneously in the fused image. As increase in spectral quality in the multispectral image is much difficult due to blur effect in spectral images, so the construction of the low resolution spatial image is a better solution [54]. Low panchromatic has much less resolution than the input panchromatic image. Resolution of the panchromatic image is decreased by comparing it to the resolution of the multispectral image [55]. Filters generate low resolution spatial panchromatic images and these images are merged with the multispectral images to achieve the better spatial and spectral qualities in the final fused images [55]. Filters should be designed in a way that the low resolution panchromatic images must possess all the information of the panchromatic input images [2]. In filter based techniques, low resolution panchromatic creation should be as fast as possible [56].

Rahmani et al. proposed an improved version of IHS image fusion [39]. In this technique, the spectral quality of the fused image is improved using two new modifications [39]. First, the image adaptive coefficients for IHS are proposed to obtain more precise spectral resolution. It also proposed an edge-adaptive IHS method which enforces the spectral fidelity in the edges [39]. The adaptive IHS method produces the final fused images of high quality as compared to the original IHS in terms of the spatial resolution and the spectral resolution [39].

Mahyari et al. proposed similarity measurement model for the fusion [54]. In this technique, the spectral histogram is used to characterize the spectral information of the multispectral image in different frequency ranges [54]. Similarity between two spectral images is measured through the similarity measurement techniques. The fourth-order correlation coefficient is used for the spatial similarity between images [54]. In fusion level decision process, the spatial information is injected into the multispectral image on the bases of a proper threshold [54]. There is no reference to choose a specific threshold. Threshold is calculated separately for each set of the input images. Threshold is based on intersection of two similarity curves [54]. The spatial and the spectral similarities are calculated and then input images are decomposed using the non-subsampled contourlet transform. Panchromatic details are injected into the multispectral details considering the threshold [54].

Zhu et al. proposed a new satellite image fusion method named Sparse Fusion of Images (SparseFI, pronounced as "sparsify") [55]. This technique is based on the theory of compressive sensing. In this technique, the sparse representation of the low resolution multispectral image is patched in the dictionary pairs. This dictionary is constructed from the panchromatic image and its down-sampled low resolution version [55]. In general, this method has better performance as compared to the traditional methods of image fusion [55]. Sparse signal reconstruction algorithms have super-resolution capability and robustness. Spectral composition model for the panchromatic image is not assumed in SparseFI [55]. In most of the cases, this technique produces the better spatial quality of the fused image and comparable spectral results as compared to the traditional methods [55].

Kim et al. proposed a filter based image fusion approach for satellite images [56]. The radiometric information is preserved by injecting the high frequency of the panchromatic image follow by the frequency of the multispectral image. An improved additive-wavelet (AW) fusion method is presented in this technique by using the à trous algorithm [56]. In this technique, the multispectral images are not decomposed, so the radiometric information of the multispectral image remains preserved and can inject high frequency following the frequency of the multispectral image using a low resolution panchromatic image [56].

Shahdoosti et al. proposed a filter based satellite image fusion [2]. In this technique, information of the panchromatic image is optimized and injected into the multispectral image. In remote sensing field, the fused image has more persistent spectral quality and texture properties as compared to the other filter based image fusion techniques [2].

FPSQ (Fusion preserving spectral quality) is a filter based image fusion technique as shown in Table 2.1. In filter based techniques, specific filter is designed for fusion [2]. IHS and PCA suffer from spectral distortion due to the high resolution input panchromatic images as shown in Figure 2.1. But in FPSQ technique, first the resolution of the panchromatic image is decreased and then this low resolution panchromatic image is fused with the multispectral image. Low resolution panchromatic image values are fused with all bands of the multispectral image. In filter based techniques, the fused image has minimum spectral distortion and better fusion quality [2]. It has better spatial quality as compared to IHS and PCA as shown in Figure 2.1. It also overcomes the spectral contrast problem which can be observed in Brovey. Fused image of FPSQ has no blur effect and has very much similar quality to the multispectral input image as shown in Figure 2.1. Spectral quality in FPSQ is much better but it suffers in fusion quality due to some deficiencies of its filter.

Advantages

Filter based techniques are optimized image fusion techniques [55]. In satellite image fusion, these techniques increase the spectral quality and spatial quality of the final fused image [2]. These techniques improve the input images. Fusion is performed on the improved input images such as the creation of low resolution panchromatic image in the field of remote sensing [2].

Disadvantages

These techniques focus on the spectral quality and ignore the fusion quality of the fused image [55].

2.3.6 Compressive Sensing Based Methods

Compressive sensing constructs the sparse values from the input values and reconstructs the same input values from these sparse values [57]. Sparse values are much fewer than the input values [57]. Sparse values should produce at a ratio where the values must be very fewer than the input values but at least a specific amount of the sparse values should produce that can truly represent the input values [57].

Chartrand et al. proposed the iteratively reweighted least squares (IRLS) technique which recovers the more non-zero components from compressed data as compared to the un-regularized IRLS technique [58]. It recovers the data with regular iterations until the estimated non-zero components are not achieved [58].

Canh et al. proposed the signal recovery under Kronecker compressive sensing (KCS) framework using split Bregman technique [59]. In this technique, the recovery problem is divided into three sub problems and recovers each by iterative technique [59]. Eigen decomposition is applied on two sub-problems and compressive signals are calculated. Third sub-problem is solved by taking derivative and combining the solutions. Weighted matrices are designed and used to calculate the recover signals [59].

Fei et al. used the following model [60].

$$\min_{X} \|\nabla X \bullet d\|_1 + \frac{\lambda}{2} \|Y - \Phi X\|_2^2 \quad [60]$$

In above equation, vector X represents input signal which should recover in compressive sensing, iterative redefined orientation field is denoted with d, Y is corresponding measurement vector and ϕ is CS measurement matrix [60].

Canh et al. proposed a well optimized scheme. In this methodology, single iteration improves the recovery performance while for optimal recovery; results need some more iteration depending on the nature of the sparse signals [60]. Sparse signals are not true images but they can be used efficiently for the calculation purposes [60]. Complex calculations can be easily performed on these signals that help to decrease the complexity of complete function [60]. Compressive sensing signals are also used in image fusion calculations [60].

Compressive sensing can be implemented through following methodologies.

2.3.6.1 Iteratively Reweighted L1 Minimization

It depends on weighted formulation and designed to interdict non-zero coefficients more efficiently [59]. Appropriate weights are constructed using iterative calculations [59]. This technique can be implemented in a variety of ways by setting existed and mature programming languages. A few steps required to implement this technique due to its simple nature [59]. It works on a simple algorithm of reweighted rule [61]. It does not provide an optimal sparse solution [59]. Large number of calculations slows down the speed of algorithm [61].

2.3.6.2 Edge Preserving Total Variation Based CS

This is a two-step iteration progression in which forward and backward iterations are used [60]. Process stops when either the numbers of iterations are completed or compressive values are achieved [60]. It has less iteration than the conventional way to produce the compressive signals [61]. It has higher correlation between the values than any other compressive sensing method because it has negligible or minor fluctuations at the non-edge points [60]. It can easily understand and preserve the value of sharpness at edges [61]. In reconstruction, it degrades the image resolution to some extend [61].

2.3.6.3 Iterative Directional Orientation Field and Total Variation

Approximate minimizer for getting compressive values is fashioned in this technique [60]. Iterative process gets values from the input signals until the convergence on compressive values is achieved [60]. It can easily estimate the noisy points. Sharpness of the image is well understood in the process of estimation of signals [60]. Accurate and robust image can be easily created through this technique. It can reconstruct noiseless images [61]. It prevents the over-smoothing and maintains the texture details [60]. Noisy orientation of image can be redefined pretty easily [60]. It can preserve image quality as compared to other iterative methods [61]. Number of directionless pixels in flat areas of images is increased. In the regions of edges, field inconsistency can be observed [61].

2.3.6.4 Compressive Sensing Based Satellite Image Fusion

Compressive sensing based image fusion is a new field. In this process, input images produce sparse signals which are fewer than the input signals but contain all essential attributes of input images [61]. Sparse signals are generated and calculations of image fusion are performed on those signals. In this technique, very few signals provide the same results of calculations as complete image signals provide on large number of calculations [59]. This is a novice technique. Fusion process is performed on the calculated results of compressive signals. These very few signals can easily brought back the input signals [59]. This reconstruction process requires input images and compressive values of merged image to make a decent fused image [60]. Reconstruction process is very slow and requires more calculation time [59].

In satellite image fusion, the panchromatic image has single band. Compressive values of one band are generated and used them for calculation purposes. But the multispectral image has three or more bands in which compressive values for each band are separately calculated. Compressive values of every band of multispectral image are combined so that the combined compressive signals can represent the multispectral image [21]. Compressive signals of both input images have much less quantity as compared to the image values. Quantity of compressive signals can be defined easily as a ratio of input values [62]. An optimal value of the ratio is selected for each fusion process but that ratio remains the same for producing compressive signals for every input image [62]. There are very few implementations of image fusion that use this technique. Some compressive sensing based satellite image fusion approaches are discussed in Table 2.2.

Table 2.2: CS Based Satellite Image Fusion Techniques [21, 59, 62, 63, 64]

Technique	Year	Results	Complexity
Satellite Images Fusion Based on Compressed Sensing and PCA [21]	2013	Greatly optimized fused image is produced, mean entropy, mean correlation and average gradient are improved.	More calculation time is required in CS based fusion of images

Remote Sensing Image Fusion Algorithm Based on Compressed Sensing [59]	2015	Get fused image with reduced dimensionality and constructed the signal with better way to make a fused image.	Fusion process is very slow due to calculation time of CS.
Remote Sensing Image Fusion Using Ripplet Transform and Compressed Sensing [62]	2015	It produces the better fusion quality in fused images. Spatial and spectral qualities are well preserved in the fused image.	It is difficult to localize the ripplet functions in the frequency domain for some processes. Moreover, the redundancy ratio remains high in ripplet.
A Compressed Sensing Based Approach for Remote Sensing Image Fusion [63]	2016	It has improved the spectral quality in the edges of the fused image. Blur effect has been minimized in the fused image.	It losses the details of input images in case of discontinuous images. It increases computational time in reconstruction.
Compressive Sensing Based Pan-sharpening Method [64]	2012	It improves the quality of the fused image.	It is slow in computations. Compressive sensing takes much time in the reconstruction of signals.

W. Yang et al. proposed compressive sensing based image fusion technique [21]. Compressive sensing leaves the full sample for fusion and moves the sampling of the signal to sampling information that significantly decreases the potential usage of traditional signal attainment and processing [21]. In this technique, compressed sensing is combined with remote sensing image fusion technique [21]. An innovative fusion algorithm (CS-FWT-PCA) is proposed and Hama Da matrix is used as the measurement matrix and SAMP is used as the reconstruction algorithm [21]. This technique adopts an improved fusion rule which is based on the local variance [21]. This technique produces better fusion results in the field of remote sensing [21].

Q. Yang et al. proposed an improved fusion algorithm of compressive sensing for the processing of satellite image fusion [59]. In this technique, the input images are sparsely represented by using wavelet transform and the image dimensions are measured with the observation matrix in the proposed fusion algorithm [59]. Image fusion process is completed in compressive sensing domain. Finally, the improved OMP algorithm is used for the reconstruction of the fused image [59]. The improved fusion algorithm produces the fused image with very few measurements of the compressive sensing [59].

Ghahreman et al. proposed the new compressive sensing based satellite image fusion [62]. The ripplet transform simplifies the curvelet transform. The ripplet transform adds two parameters in the curvelet transform [62]. Anisotropy capability of representing singularities is achieved through added parameters of the ripplet transform [62]. In this technique, the spatial details are extracted from the panchromatic images by using means of ripplets and these details are injected into the multispectral images by using compressive sensing based injection methodology [62]. The aim of this compressive sensing based methodology is to minimize the spectral distortion in the final fused image [62].

Khateri et al. proposed a compressive sensing based pan-sharpening method [63]. In proposed technique, the high resolution panchromatic and the low resolution multispectral dictionaries are learned from the input images [63]. In proposed technique, information of non-overlapped patches is extracted from the input images. Initial estimate for the fused image is constructed from the information of input images [63]. Initial dictionaries of the high resolution panchromatic image and the low resolution multispectral image are used to construct the fused image [63].

Jiang et al. proposed a new compressive sensing based satellite image fusion method. Image observation model is used as a measurement process in the theory of compressive sensing and creates a joint dictionary from the high resolution panchromatic and the sparse low resolution multispectral images [64]. Real remote sensing images are fused with the compressive sensing based methodology to produce the fused images with good quality [64].

Advantages

These techniques efficiently improve the fusion quality by removing the redundant signals of input images [63].

Disadvantages

Reconstruction from the compressive sensing values increases the computation cost [64].

2.4 Fusion Quality Measurements

Fusion quality improvement is very important in the field of image fusion [65]. Multiple image fusion approaches are used in the field of satellite image fusion. Some of them more focus on the spatial details to preserve the information of panchromatic images; some other filter based approaches emphasis on minimizing spectral distortion [65]. Fusion results of all these techniques can be judged through different measurement methods. Each fusion quality measurement method has its own frame of reference for the evaluation [65]. Image fusion quality is measured in following three aspects.

2.4.1 Visual Assessment

In the field of remote sensing, the final fused images are judged visually by the experienced persons of this field [66]. Fused image with more spatial quality and less spectral quality may look very good to a lay man because these images have sharp edges and the objects are very well recognized in these images. But in the opinion of an expert, these images have miserable spectral quality because they don't represent the true colors of the input multispectral images. Image may have less spatial quality but it must represent the each input image [66]. Final fused image should have less spectral distortion and less feature dominance [66].

2.4.2 Spectral Quality

Many image fusion algorithms suffer from spectral distortion [67]. In the field of remote sensing, spectral quality is very important factor to evaluate the image fusion algorithm [67]. A good image fusion method will lead to minimum spectral distortion [67]. Spectral quality is observed through different spectral quality measurement methodologies. These types of algorithms take two input images. One image is the multispectral input image and other is the final fused image. In the field of remote sensing, this assessment is done by comparing the multispectral image with the fused image [67]. High spectral quality of the final fused image ensures that the fusion process has preserved the color information [67]. Fusion quality is not the part of spectral quality evaluation [67].

2.4.2.1 ERGAS

Relative global-dimensional synthesis error (ERGAS) is a radio metric distortion index [67]. It is used for the comparison of spectral quality of two images. This technique is highly reliable for calculation of spectral distortion [2]. As its name indicates, it calculates the normalized error of fusion process in terms of spectral quality difference between the fused image and the multispectral input image [67]. Low value of this method indicates the better spectral quality of the fused image and verifies that the colors of the final fused image and the input multispectral image are much similar [67]. It is also called spectral ERGAS [67].

$$E_i = F_i - MS_i \text{ [67]}$$

$$\Sigma\,(E_i) = \Sigma\,(F_i) - \Sigma\,(MS_i) \text{ [67]}$$

where E_i is calculated ERGAS value for $_i$th band, F_i is $_i$th band value of fused image; MS_i represents the $_i$th band value of multispectral image. Sum of all bands is also calculated for ERGAS [67].

ERGAS value can be calculated for each band of the fused image. Value of a band of multispectral image is subtracted from respective band of the fused image [67]. Value for all bands of the fused image is summed up and the sum of values of all bands of the multispectral image is subtracted from it [67]. This value is called total ERGAS value [67]. Other way for ERGAS calculation is to consider a constant value for the input multispectral image and get respective ERGAS value for the final fused image [67].

2.4.2.2 CC

Correlation coefficient (CC) enumerates the relation and dependency between the two images [67]. It will have higher value for good relational images and lower value for two different images [67]. In the field of remote sensing, it is used for the spectral quality measurement. It is used to investigate the relationship between the multispectral input image and the final fused image [67]. Standard value of correlation coefficient is 1. Value of the final fused image is compared with standard value [67].

$$CC = \frac{\Sigma\,(F_{ij}, F_{mean})\,\Sigma\,(MS_{ij}, MS_{mean})}{\sqrt{\Sigma\Sigma\,(F_{ij}, F_{mean})^2}\,\sqrt{\Sigma\Sigma\,(MS_{ij}, MS_{mean})^2}}. \text{ [67]}$$

where CC is the correlation coefficient, F represents the fused image, MS is the multispectral input image, i and j are pixels [67].

2.4.3 Fusion Quality

Fusion quality is one of the important factors in terms of fusion process assessment [65]. Value of fusion quality determines that how much information of all the input images is persevered in the fused image [65]. Final fused image must contain the information from each input image without dominance of any particular image and should have minimum spectral distortion [65]. Many algorithms have been devised for fusion quality inspection. All algorithms based on this technique accept two or more input images and a fused image [66]. Fused image information is compared with every participated input image and an average value of resemblance between the fused image and input images is calculated [66]. Fusion quality will be much better if the fusion process has less feature dominance and well preserved the quality of each input image in the fused image [66].

2.4.3.1 Feature Extraction Methods

Feature extraction methods are used for fusion quality assessment [66]. Image has particular features such as size, edges, colors, sharpness etc. Features are extracted from the pixels of all input images and the final fused image [66]. These methods compare the similarity through feature values of the input images and the final fused image [66]. Feature extraction matrices are divided into different types of techniques. Pixel based feature extraction technique, Wavelet based feature extraction technique and Gradient based feature extraction technique are some feature extraction techniques. Marginal probability function is used to get the mutual information from these extracted features of different techniques [66].

$$P\,(f) \text{ compares to } P\,(m) + P\,(f) \text{ compares to } P\,(p) \text{ [66]}$$

In above equation, P denotes the probability function, f represents the fused image, m denotes the multispectral image and p shows the panchromatic image [66].

Marginal values are calculated on the two images. Features of the fused image and the input images are compared through probability function [66].

$$P\ (f, m)\ \text{and}\ P\ (f, p)\ [66]$$

In above equation, P represents the probability function, f is the fused image, m is used for the multispectral image and p denotes the panchromatic image [66].

This type of metrics depends on the adopted technique for the feature extraction [66]. These metrics are good to evaluate the fusion quality in the field of remote sensing [66]. In these techniques, probability is devised in a way that the spectral quality must not compromise in the final fused image [66]. Probability function value for the fused image and the multispectral image must be much higher than the probability function value for the fused image and the panchromatic image [66]. It ensures that the minimum spectral distortion is achieved with the maximum fusion quality by retaining the information of the spatial and the spectral qualities of the input images in the final fused image [66]. In these methods, high value indicates the better fusion quality and low value indicates less fusion quality [66].

2.4.3.2 Mutual Information

Mutual information quantifies the amount of similar information between two images [68]. This technique measures the shared information between the final fused image and the input images. This methodology works on the theory of intersection [69]. In the field of remote sensing, common information between the fused image and the panchromatic image and common information between the fused image and the multispectral image is calculated separately [69]. A mathematical value from both procedures is generated and an average is calculated to get the shared information between the input images and the fused image [68]. In satellite image fusion process, the final result of the mutual information is compared and evaluated with following equation.

$$\frac{M.I\ (f, m) + M.I\ (f, p)}{2}\ [68]$$

In above equation, M.I is the mutual information calculation function, f is the final fused image, m shows the multispectral input image and p represents the panchromatic input image.

In mutual information technique, high value indicates good fusion quality in the fused image and low value represents less fusion quality of the fused image [68].

2.5 Summary

This chapter has particularly discussed the image fusion and compressive sensing. The important factors of the image fusion are explained in this chapter. These factors affect the quality of the final fused image. Input sensors of the remote sensing field are briefly explained. Different image fusion methodologies are described in detail. A comparative analysis of satellite image fusion techniques has been discussed. Filter based image fusion techniques have been explained in this chapter. Different compressive sensing techniques are discussed in detail. Compressive sensing based satellite image fusion techniques are also explained in this chapter. This chapter enlightens the fusion quality measurement techniques. Spectral quality measurement techniques and spatial quality measurement techniques are separately discussed in this chapter.

Proposed Method

Image fusion suffers from multiple scarcity issues. In satellite image fusion, final fused image is evaluated in terms of spectral quality and fusion quality. Spectral quality is similarity between the final fused image and multispectral image [2]. Fusion quality is evaluated by comparing the information of the final image and information of the input images [65]. Fused image must possess the information of every input image without degrading the spectral quality [66]. Satellite image fusion process is shown in Figure 3.1.

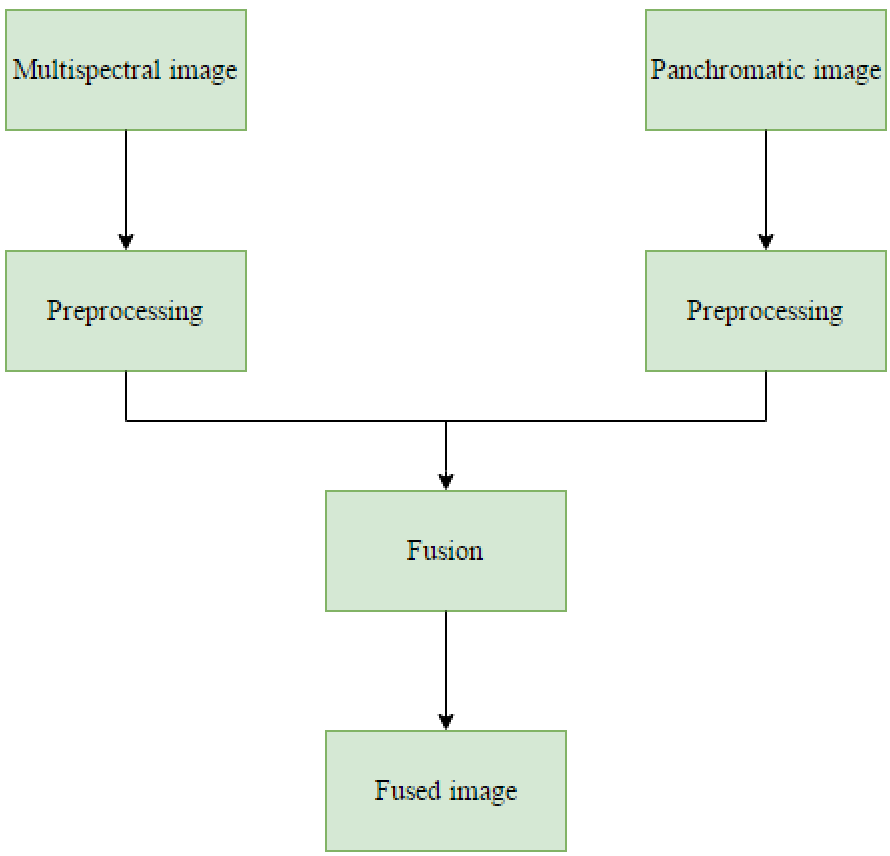

Figure 3.1: Satellite Image Fusion

3.1 Proposed Technique

A compressive sensing and filter based image fusion method is proposed for satellite images. The proposed method consists of input image values, construction of compressive sensing signals, calculation of regression coefficients, formation of optimal filter, generation of low resolution panchromatic image and fusion of multispectral and low resolution panchromatic images. Different steps of proposed technique are shown in Figure 3.2.

3.1.1 Input Values

Proposed image fusion method performs fusion on two input images. One is panchromatic image and other is multispectral image as shown in Figure 3.2. In proposed methodology, three input values are mandatory. First input is the multispectral image of type double, second input is the panchromatic image of type double and third input is a numeric value that varies from 1-10. User must provide the numeric input between suggested values to achieve better fusion results. Numeric input can be a fractional or whole number. If resolution difference between input images is low, low value of numeric input will provide better fusion results and vice versa.

3.1.2 Compressive Sensing Signals

Compressive sensing signals are generated for each input image as shown in Figure 3.2. Generated CS values are much fewer than the values of the input image [58]. Compressive sensing signals are generated by removing non-zero values from the input image values [58]. Compressive sensing signals must represent the input values. Number of compressive signals can be represented as a specific percentage of input image values [58]. In the field of remote sensing, minor details of input images are very important so a high percentage of compressive signals are generated for satellite images as compared to other imagery [58]. In proposed technique, generated compressive sensing values are 40% of the input image values, which is less than half of the input image values. Compressive sensing signals are generated for both the multispectral and panchromatic images.

3.1.2.1 Block Based Compressive Sensing

In proposed methodology, block based compressive sensing technique is adopted to generate the compressive signals. A specific block size is selected for the compressive values [58]. Depending on the block size, projection of the input image is created [58]. Block size must not be very large number to extract the information from input images because with high value, it will not extract the fewer signals from the input signals [57]. In implementation of proposed technique, the block size value is 32. In case of panchromatic image, the projection is created for the complete image which represents as a copy of the input image. It produces a sensing matrix [57]. Compressive signals are calculated for the panchromatic image projection based on selected block size and selected percentage [58].

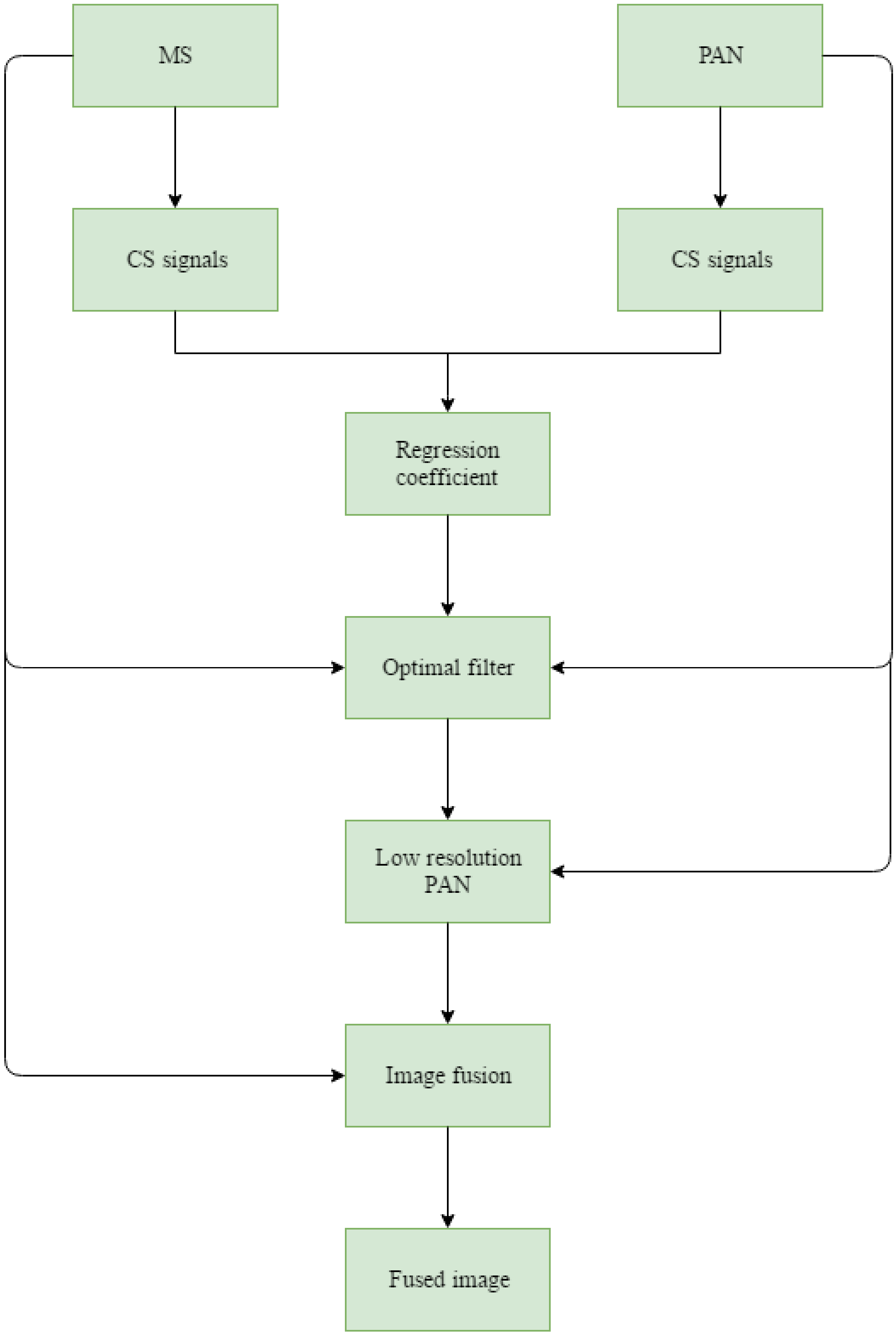

Figure 3.2: Proposed Method

Orthonormal basis are used in calculation of compressive sensing signals [59]. Distinct observed measurements are calculated for panchromatic image. Distinct observed measurements are based upon block size [58]. In the same manner by using projection and distinct observed measurements, compressive signals are calculated for each band of multispectral image. Compressive sensing values of each band of multispectral image are concatenated for using in calculations [58].

$$CS = Proj\ (P) * Observed\ Measurements\ (P)\ [58]$$

$$CS_i = Proj\ (MS_i) * Observed\ Measurements\ (MS_i)\ [58]$$

where CS represents compressive sensing values for panchromatic image, Proj (P) is a sensing matrix for panchromatic image, Observed Measurements (P) are distinct calculated values for the panchromatic image, CS_i represents the compressive sensing values for the $_i$th band of multispectral image, Proj (MS_i) is a sensing matrix for the $_i$th band of multispectral image and Observed Measurements (MS_i) are distinct calculated values for the $_i$th band of multispectral image [58].

Calculated Compressive sensing values are further used for the calculation of regression coefficient.

3.1.3 Calculation of Regression Coefficients

Regression coefficients are calculated between the panchromatic image and each band of the multispectral image as shown in Figure 3.2. Regression coefficients value for each band of the multispectral image can be different [2]. In proposed methodology, a new optimized symmetric value matrix is designed for compressive values. Regression coefficients are calculated on compressive values of panchromatic and multispectral images using the following formula [2].

$$CSP_L = Conv\ (CS\ (P), M)\ [2]$$

$$RF_i = Cov\ (CS\ (MS_i), CSP_L)) / Var\ (CSP_L)\ [2]$$

In equations, CSP_L represents low pass filtered panchromatic image values; CS (P) denotes compressive sensing values for the panchromatic image, M is devised symmetric value matrix for convolution calculation, RF_i is regression coefficient value for the $_i$th band of multispectral image, CS (MS_i) represents the compressive signals for the $_i$th band of multispectral image [2].

In proposed technique, numeric input value normalizes the level of low pass filtered panchromatic image and devised symmetric value matrix. If high resolution panchromatic input image is used in fusion process then high value of numeric input parameter will create good low pass filtered image for fusion process [2]. If low resolution panchromatic input image is used in fusion process then low value of numeric input parameter will generate the better fusion results

[2]. Sum of regression coefficient values should be 1 to achieve the better spectral and spatial qualities in the fused image [2]. Main constraint on each regression value is that it should neither be negative nor be greater than 1 because if it is more than 1 then the edges of the fused image will be sharper than the panchromatic input image [2]. Negative value of regression coefficients for any band of the multispectral image indicates less spatial quality in the fused image which decreases the fusion quality in the fused image [2]. In proposed methodology, the devised symmetric value matrix and numeric input value keep the values of regression coefficients in between 0.25 and 0.40. Regression coefficient values decrease the sharp edges in panchromatic image for achieving the better fusion results. Panchromatic image with less sharp edges does not distort the colors of input multispectral image in the fused image [2]. In proposed technique, despite of deviation in each regression coefficient value, their sum has been achieved very close to 1.

3.1.4 Formation of Optimal Filter

An optimal filter for image fusion is adopted in the proposed technique. A vector of size 49 (7*7) is created for panchromatic image. Optimal filter is constructed by using vector size, regression coefficients and input multispectral and panchromatic images using the following formula.

$$H = \left(2\sum_{i=1}^{N}\frac{G_i^2 C_P}{m_{\mathrm{MS}_i}^2}\right)^{-1} \times \left(\sum_{i=1}^{N}\frac{G_i^2 C_{P,\mathrm{P}} + G_i C_{P,\mathrm{MS}_i + G_i\mathrm{F}-\mathrm{P}_i}}{m_{\mathrm{MS}_i}^2} + 0.5\lambda O\right) \quad [2]$$

where H represents the Optimal filter, G_i is the ith band regression coefficient, C_P is the correlation matrix of vector *P*, $C_{P,\mathrm{P}}$ denotes the cross correlation between vector *P* and panchromatic image, $C_{P,\mathrm{MS}_i+G_i\ \mathrm{P}-\mathrm{P}_i}$ is the cross correlation between vector *P* and $\mathrm{MS}_i+G_i\ \mathrm{P}-\mathrm{P}_i$, λ is obtained from the invariance of C_P. *P* is vector of size 49, MS_i is the ith band multispectral input image and P is panchromatic input image [2].

Optimal filter of size 49 (7*7) produces the good fusion results. Filter size greater than this size does not help to improve the quality of the fused image [2]. Filter size should be small because improvements with large filter size are not acceptable in the field of image fusion because it increases the calculation cost [2]. Optimal filter calculations depend on the regression coefficient values. Optimal regression coefficient values lead to construct the optimal filter [2].

3.1.5 Generation of Low Resolution Panchromatic Image

Low resolution panchromatic image is created from the input panchromatic image and optimal filter as shown in Figure 3.2. In satellite image fusion, multispectral image has comparatively low resolution as compared to the panchromatic image [2]. In proposed methodology, a low resolution panchromatic image with less sharped edges is created to achieve the better fusion results. Regression coefficient values and optimal filter decide the level of low resolution panchromatic image [2]. Low pass panchromatic signals are generated by using the optimal filter and the panchromatic vector of size 49 (7*7). Low pass signals are subtracted from the input panchromatic image to generate the low resolution panchromatic image.

$$P_{LR} = (P - P_{LP})$$

In above equation, P_{LR} represents low resolution panchromatic value, P is input panchromatic image value and P_{LP} is low pass panchromatic value.

3.1.6 Fusion of Multispectral and Low Resolution Panchromatic Images

After creation of low resolution panchromatic image, low resolution panchromatic image is injected into the multispectral image as shown in Figure 3.2. Product of low resolution panchromatic image and regression coefficient is calculated for each band of multispectral image and added into the respective band of multispectral input image.

$$F_i = MS_i + RF_i * (P - P_{LP}) \text{ [2]}$$

Equation represents the process of adding panchromatic values into the multispectral values, where F_i represents the $_i$th band of final fused image, MS_i is the value of $_i$th band of multispectral image, RF_i shows the regression coefficient value for $_i$th band of multispectral image, P denotes the real panchromatic image value and P_{LP} represents the low resolution panchromatic image [2].

3.1.7 Fused Image

Final fused image is obtained by injecting the low resolution panchromatic image into the multispectral image as shown in Figure 3.2. Number of bands in the final fused image is equal to the number of bands in the multispectral input image. In proposed technique, the final fused images have better fusion quality and have minimized the spectral distortion as compared to the traditional techniques of satellite image fusion. Final fused image persist the spectral quality of the multispectral input image and the spatial quality of the panchromatic input image.

3.2 Summary

This chapter is an overview of a compressive sensing and filter based satellite image fusion technique. This chapter has thoroughly discussed the steps of proposed image fusion technique. Input values and their impact in proposed technique have been briefly discussed. Block based compressive sensing has been explained in this chapter. Regression coefficient and its importance in proposed technique have been described. This chapter has enlightened on the formation process of optimal filter and generation of low resolution panchromatic image. Fusion of multispectral image and low resolution panchromatic image has been explained in this chapter. Finally, the final fused image has been discussed in this chapter.

Results and Analysis

Proposed method has provided much better fusion results than any previously suggested models. Different experiments are performed to verify this statement. For proving effectiveness, results are validated by using two different types of quality measurements. Ten different multispectral and panchromatic images are fused by using four different methods and proposed method. Each fused image of other techniques is compared with proposed method's fusion result by using two spectral quality measurement techniques and four fusion quality measurement techniques.

4.1 Spectral Quality

Spectral distortion can be calculated through different methods but two most prominent methods are relative global-dimensional synthesis error (ERGAS) and correlation coefficient (CC) [70]. ERGAS is a radio metric distortion index [70]. Visual quality valuation with high reliability can be done by using this method [70]. Low value of this method ensures that the spectral quality of the fused image is much better and the colors of the fused image are very similar to the multispectral input image [70]. Correlation coefficient compares the fused image with the multispectral image. It determines the value of similarity between the final fused image and the multispectral input image [70]. High value of this method indicates that the fused image and the multispectral input image have more similar spectral quality [70].

4.2 Fusion Quality

Fusion quality can be determined by using different algorithms but some fusion quality measurement methods ignore the spectral distortion and rely on input images [69]. Feature mutual information methods determine the fusion quality as well as the spectral distortion [69]. Pixel level feature extraction determines the quality of fusion for every pixel of the input images and the fused image [69]. Wavelet level feature extraction depends on norm entropy and classifier based multi-layer perception to determine the features of the final fused image [69]. Fusion quality in wavelet level feature extraction is evaluated between the input images and the fused image by using the spatial and the spectral details [69]. Gradient based feature extraction method depends on change in intensity and color of image [69]. It compares the spectral change between the fused image and the input images. Mutual information methodology compares the features of input images with the features of fused image [68].

4.3 Experiments

Following ten experiments are performed on different input images for supporting the proposed methodology. Each result shows that the proposed methodology has been achieved better results than any existing technique. In all experiments, image (A) is input panchromatic image and image (B) is input multispectral image. Image (C) is produced by using IHS image fusion technique [20]. Brovey image fusion results are shown in image (D) [23]. Image (E) represents PCA image fusion results [36]. Outcomes of FPSQ technique are presented in image (F) [2]. Proposed methodology results are displayed in image (G). Experimental results are visually presented. Spectral and spatial qualities have been measured in statistical form. All statistical results of proposed method and existing techniques are presented in tabular structure. Results clearly support the proposed technique.

4.3.1 Experiment 1

Sensor: High Resolution IKONOS

Figure 4.1: Visual Comparison of Experiment 1, P (1 m resolution, 0.45–0.90µm). MS [4 m resolution, blue (0.45–0.52µm), green (0.51–0.60µm), red (0.63–0.70µm), NIR (0.76–0.85µm)] [2, 49]

Table 4.1 Statistical Comparison of Experiment 1

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	69.1560	0.3781	0.0766	0.1226	0.0892	3.6973
Brovey [23]	25.3861	0.9262	0.0891	0.1246	0.0924	2.8882
PCA [36]	61.4034	0.3939	0.0786	0.1263	0.0907	3.2625
FPSQ [2]	16.1572	0.9712	0.1103	0.2046	0.1255	3.5115
Proposed	15.9514	0.9720	0.1113	0.2066	0.1267	3.5475

Table 4.1 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

4.3.2 Experiment 2

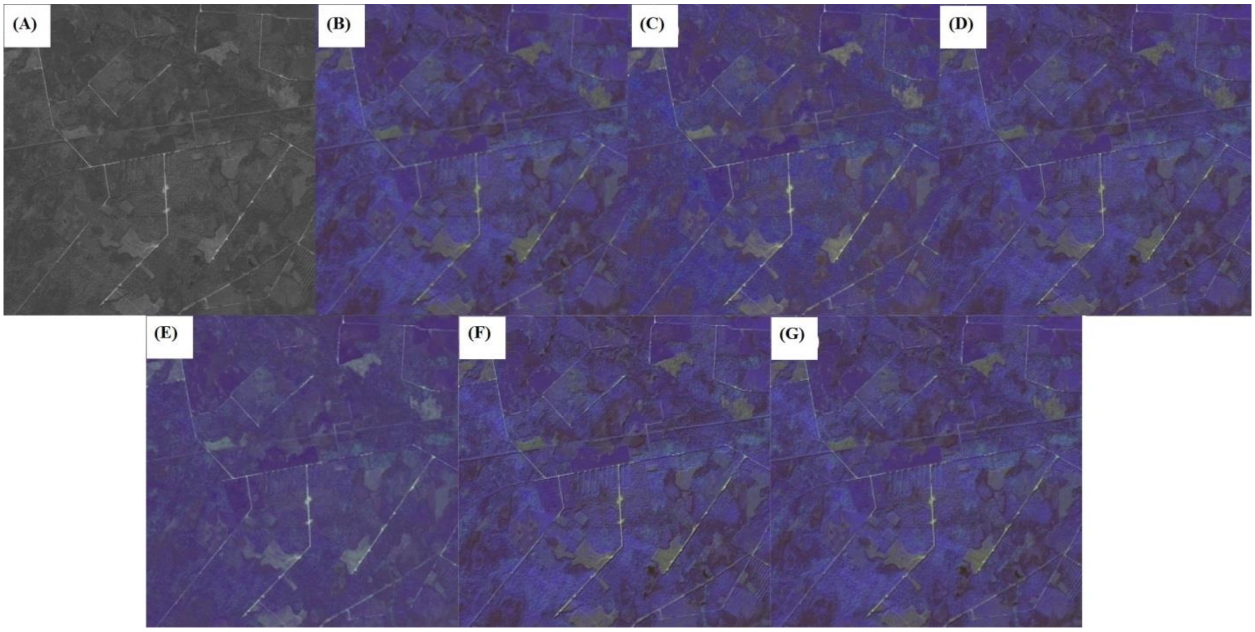

Figure 4.2: Visual Comparison of Experiment 2 [9, 10]

Table 4.2 Statistical Comparison of Experiment 2

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	9.3470	0.7980	0.1039	0.1462	0.1322	5.3531
Brovey [23]	6.6359	0.8821	0.1155	0.1600	0.1380	6.5057
PCA [36]	9.6706	0.7327	0.1059	0.1677	0.1543	5.9621
FPSQ [2]	7.4443	0.8713	0.1281	0.1931	0.1783	6.0255
Proposed	5.6877	0.9135	0.1338	0.2122	0.1922	6.4683

Table 4.2 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

4.3.3 Experiment 3

Sensor: Medium Resolution Landsat-7 ETM+

Location: Tehran Iran

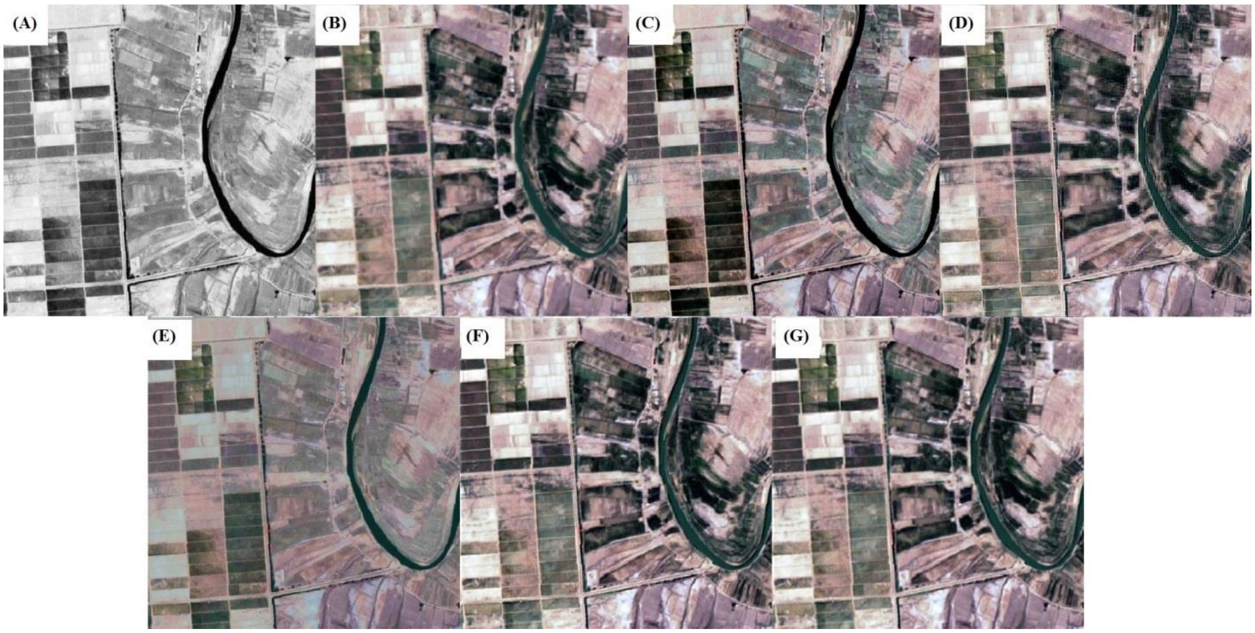

Figure 4.3: Visual Comparison of Experiment 3, P 14696 × 12416 (14.25 m resolution, 0.52–0.92µm). MS 7348 × 6208 [28.5 m resolution, blue (0.45–0.515µm), green (0.525–0.605µm), red (0.63–0.69µm) Near-IR: 0.76–0.9µm] [9, 10]

Table 4.3 Statistical Comparison of Experiment 3

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	33.4706	0.7288	0.0969	0.135	0.1098	4.1201
Brovey [23]	12.4379	0.9646	0.1106	0.1444	0.1109	3.7666
PCA [36]	32.8571	0.7220	0.0992	0.1447	0.1109	3.7112
FPSQ [2]	10.7173	0.9751	0.1360	0.2188	0.1664	4.1369
Proposed	7.5607	0.9875	0.1503	0.2614	0.1978	4.4866

Table 4.3 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

4.3.4 Experiment 4

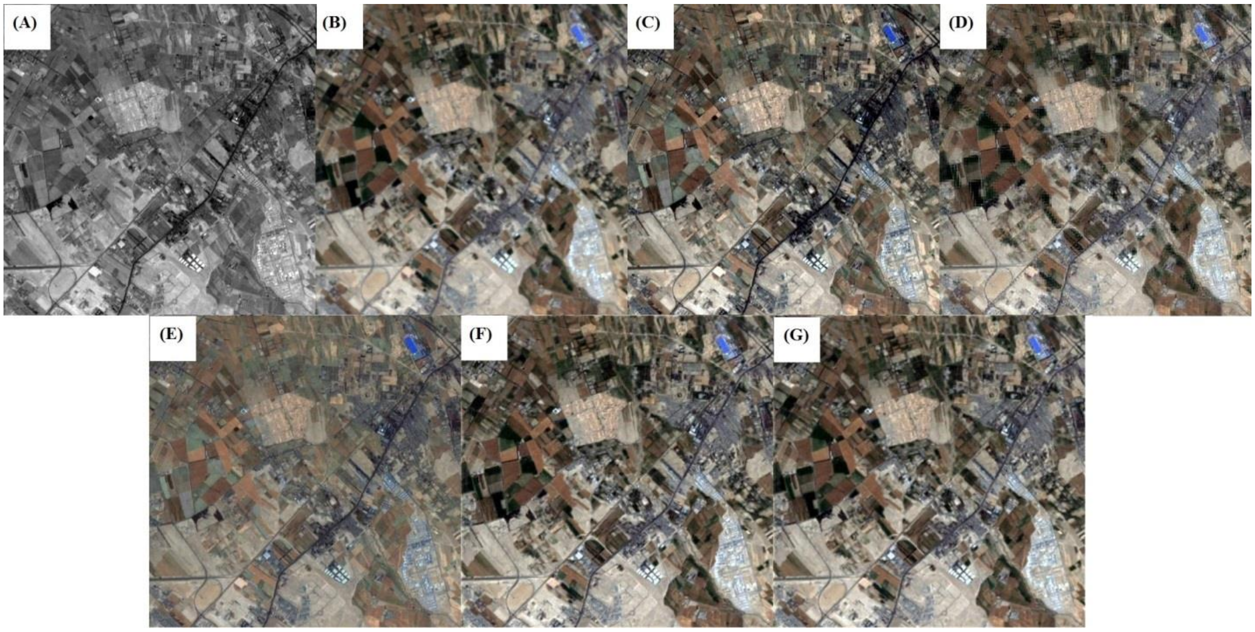

Figure 4.4: Visual Comparison of Experiment 4 [9, 10]

Table 4.4 Statistical Comparison of Experiment 4

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	29.6612	0.7841	0.0985	0.1479	0.1207	3.4459
Brovey [23]	13.0140	0.9597	0.1099	0.1512	0.1215	3.4068
PCA [36]	29.5284	0.7827	0.1000	0.1550	0.1246	2.7701
FPSQ [2]	11.3282	0.9712	0.1333	0.2212	0.1794	3.6711
Proposed	9.0381	0.9815	0.1444	0.2525	0.2075	3.9144

Table 4.4 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

4.3.5 Experiment 5

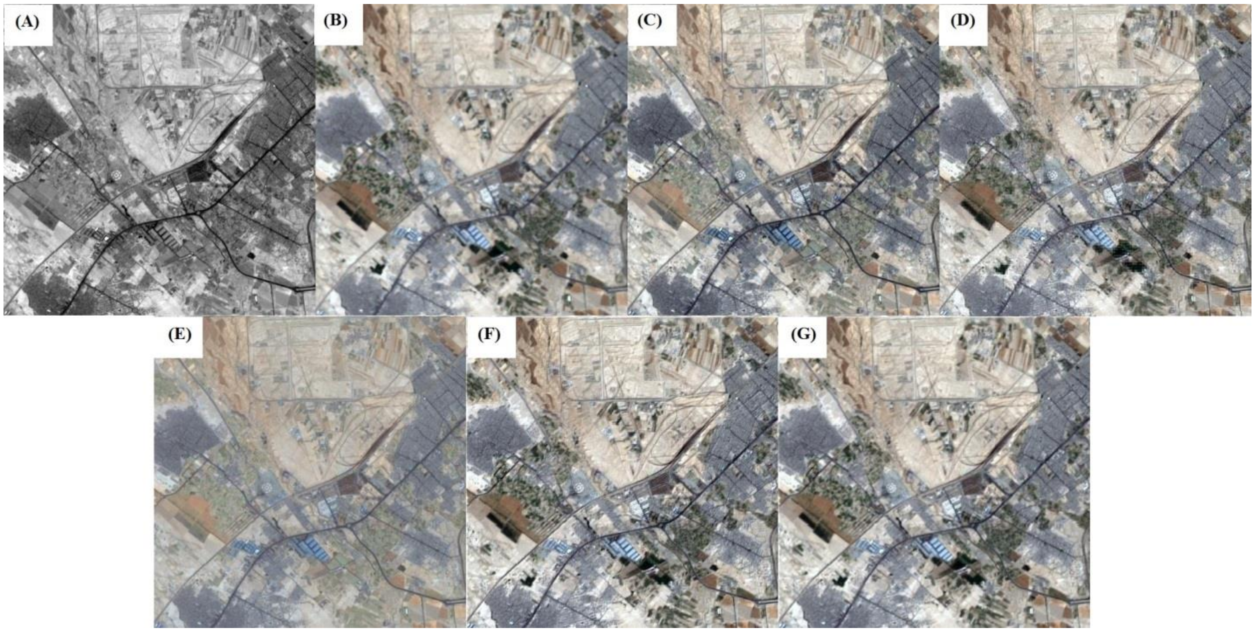

Figure 4.5: Visual Comparison of Experiment 5 [9, 10]

Table 4.5 Statistical Comparison of Experiment 5

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	16.3688	0.8338	0.1029	0.1576	0.1262	3.7269
Brovey [23]	9.7123	0.9451	0.1083	0.1525	0.1226	3.5540
PCA [36]	17.1507	0.8362	0.1026	0.1619	0.1294	2.9723
FPSQ [2]	11.6861	0.9267	0.1094	0.1670	0.1390	3.2358
Proposed	7.3862	0.9690	0.1322	0.2328	0.1918	3.9431

Table 4.5 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

4.3.6 Experiment 6

Sensor: High Resolution Quickbird

Location: Boulder, CO, USA

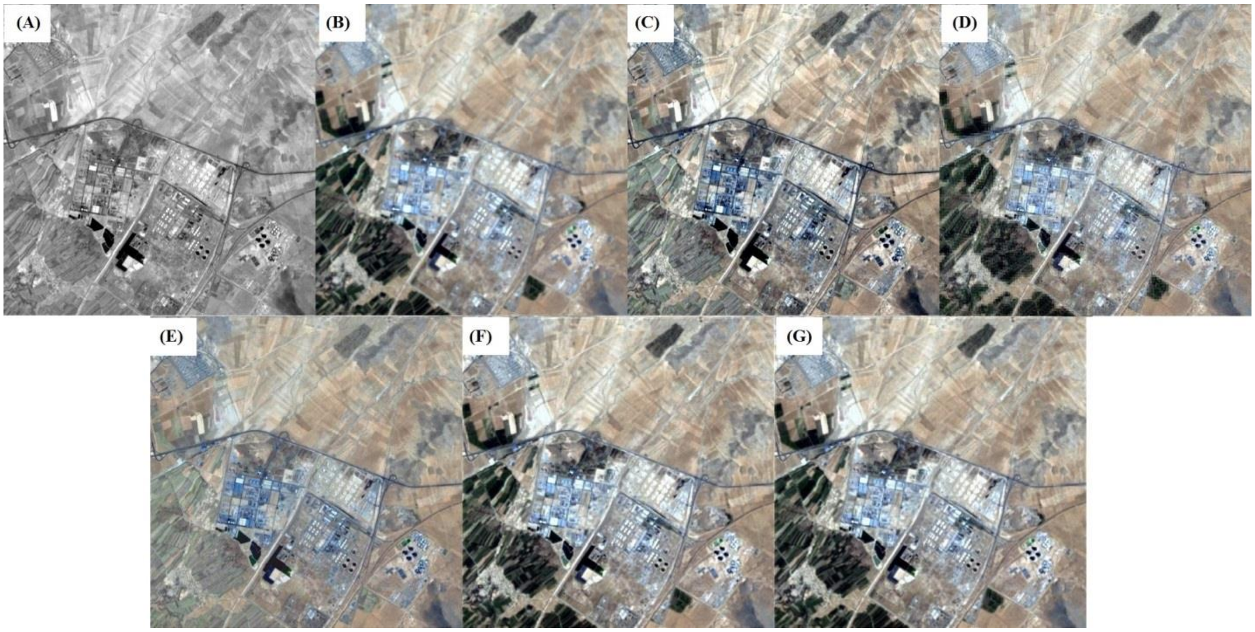

Figure 4.6: Visual Comparison of Experiment 6, P 3312 × 3260 (0.6 m resolution, 0.45–0.90µm). MS 828 × 815 [2.4 m resolution, blue (0.45–0.52µm), green (0.52–0.6µm), red (0.63–0.69µm) Near-IR: 0.76–0.9µm] [9, 10]

Table 4.6 Statistical Comparison of Experiment 6

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	24.2809	0.7235	0.1002	0.1499	0.1221	3.5565
Brovey [23]	8.8151	0.9657	0.1092	0.1543	0.1222	3.9730
PCA [36]	23.3644	0.7261	0.1021	0.1588	0.1268	2.7907
FPSQ [2]	6.6444	0.9815	0.1411	0.2420	0.1982	4.2783
Proposed	6.0707	0.9845	0.1440	0.2511	0.2052	4.3889

Table 4.6 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

4.3.7 Experiment 7

Sensor: High Resolution Wordview-2

Location: Rome, Italy

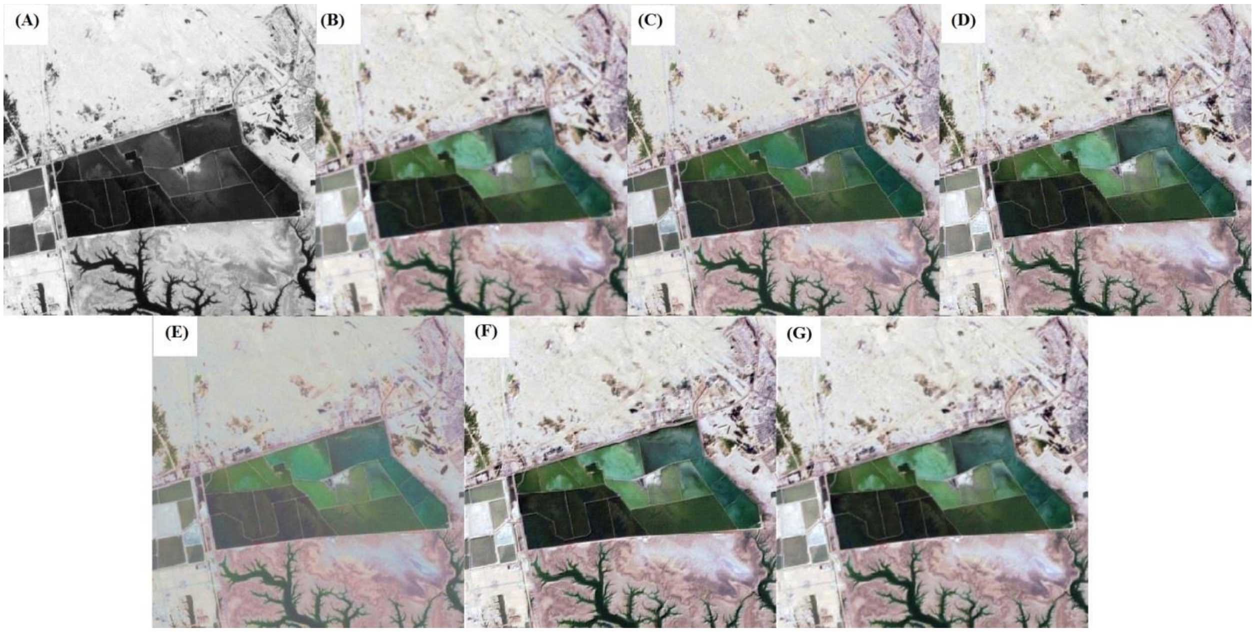

Figure 4.7: Visual Comparison of Experiment 7, P 3312 × 3260 (0.46 m resolution, 0.45–0.80µm). MS 828 × 815 [1.84 m resolution, blue (0.45–0.51µm), green (0.51–0.58µm), red (0.63–0.69µm) Near-IR: 0.77–0.895µm] [9, 10]

Table 4.7 Statistical Comparison of Experiment 7

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	12.3083	0.9522	0.0954	0.1364	0.1107	5.1873
Brovey [23]	8.2820	0.9790	0.1028	0.1375	0.1087	5.1873
PCA [36]	19.0622	0.9519	0.0952	0.1441	0.1144	4.0809
FPSQ [2]	9.6106	0.9724	0.1093	0.1539	0.1251	4.9078
Proposed	5.7723	0.9898	0.1279	0.2064	0.1602	5.5435

Table 4.7 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

4.3.8 Experiment 8

Sensor: High Resolution Quickbird

Location: Kokilai Lagoon, Sri Lanka

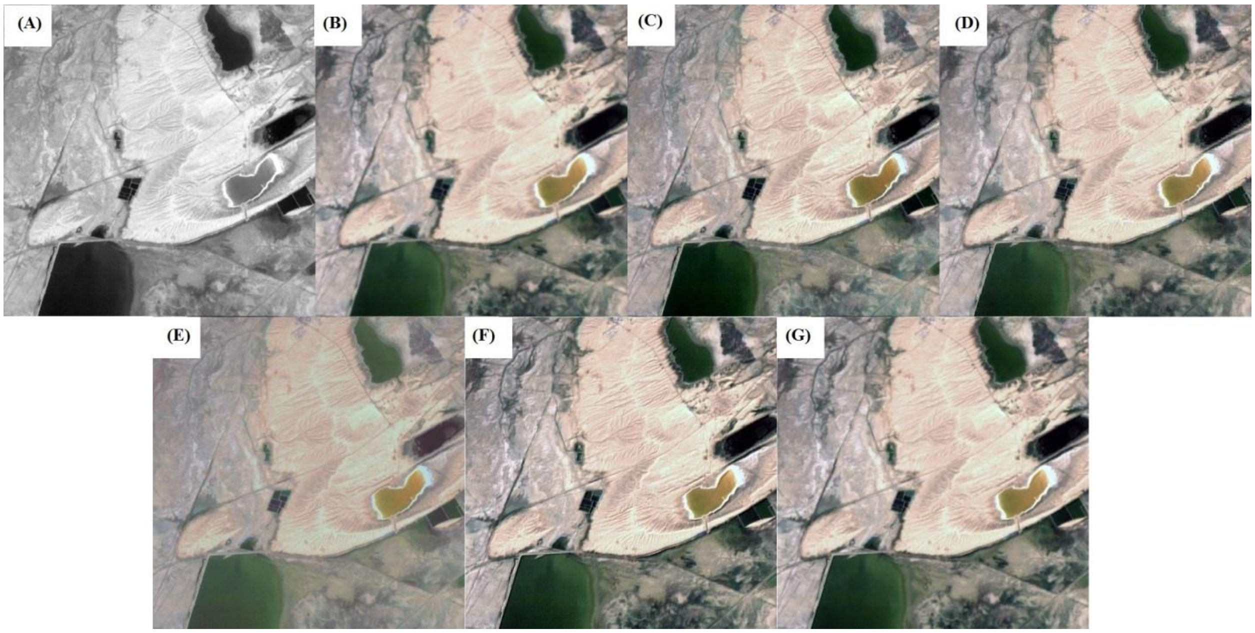

Figure 4.8: Visual Comparison of Experiment 8, P 12792 × 10668 (0.6 m resolution, 0.45–0.90µm). MS 3198 × 2667 [2.4 m resolution, blue (0.45–0.52µm), green (0.52–0.6µm), red (0.63–0.69µm) Near-IR: 0.76–0.9µm] [9, 10]

Table 4.8 Statistical Comparison of Experiment 8

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	11.7588	0.9541	0.1028	0.1517	0.1179	5.8290
Brovey [23]	5.5362	0.9899	0.1112	0.1551	0.1165	5.7774
PCA [36]	18.7128	0.9522	0.1028	0.1604	0.1220	5.2781
FPSQ [2]	8.8927	0.9753	0.1129	0.1601	0.1327	5.2001
Proposed	4.5677	0.9933	0.1339	0.232	0.1783	6.1979

Table 4.8 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

4.3.9 Experiment 9

Sensor: High Resolution Wordview-2

Location: Rome, Italy

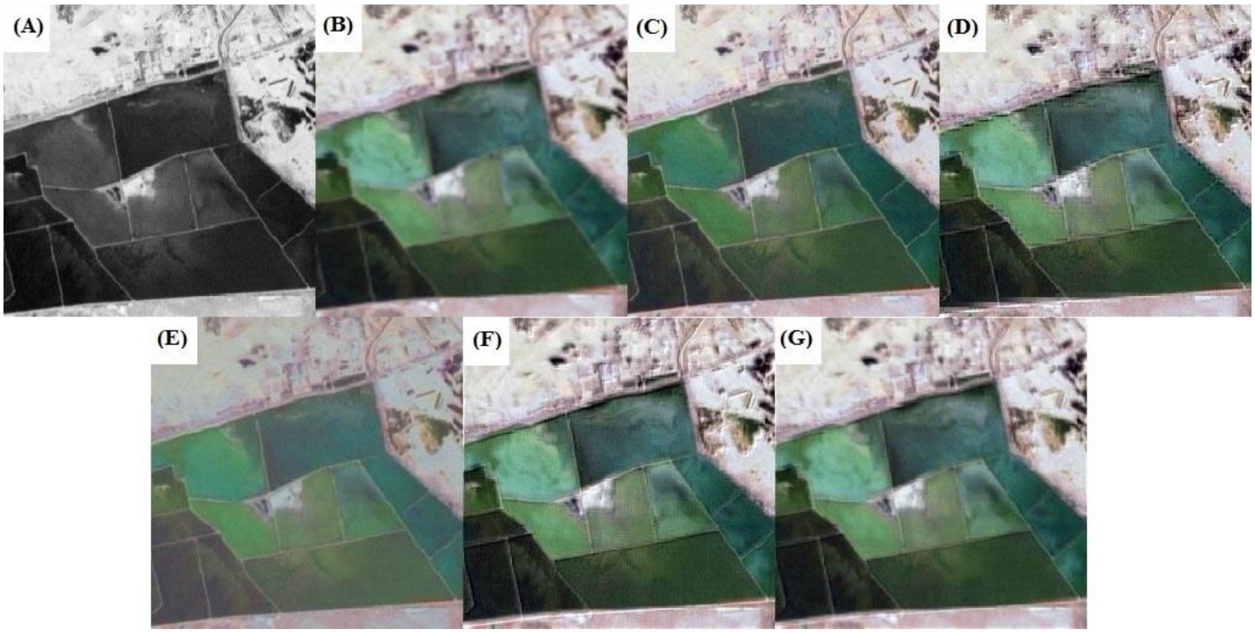

Figure 4.9: Visual Comparison of Experiment 9, Focused P 3312 × 3260 (0.46 m resolution, 0.45–0.80μm). MS 828 × 815 [1.84 m resolution, blue (0.45–0.51μm), green (0.51–0.58μm), red (0.63–0.69μm) Near-IR: 0.77–0.895μm] [9, 10]

Table 4.9 Statistical Comparison of Experiment 9

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	20.3699	0.9253	0.0851	0.1165	0.1002	4.6908
Brovey [23]	12.1889	0.9738	0.0940	0.1188	0.0986	5.3330
PCA [36]	26.9159	0.9278	0.0865	0.1277	0.1058	3.9741
FPSQ [2]	10.0846	0.9830	0.1148	0.1547	0.1229	5.2774
Proposed	6.2265	0.9933	0.1271	0.1985	0.1508	5.8901

Table 4.9 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

4.3.10 Experiment 10

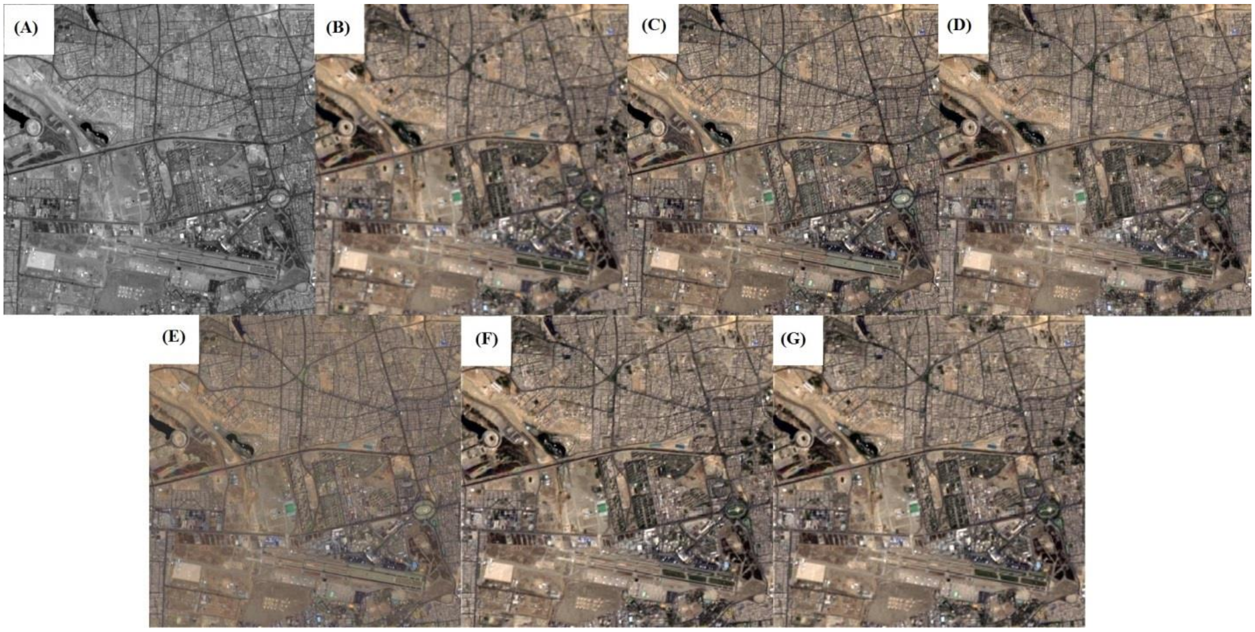

Figure 4.10: Visual Comparison of Experiment 10 [9, 10]

Table 4.10 Statistical Comparison of Experiment 10

Methods	Spectral Quality		Fusion Quality			
	ERGAS	CC	Wavelet	Pixel	Gradient	MI
IHS [20]	22.2512	0.7512	0.1040	0.1527	0.1241	3.5279
Brovey [23]	13.1231	0.9189	0.1142	0.1585	0.1248	3.1210
PCA [36]	21.3372	0.7559	0.1046	0.1551	0.1261	3.1997
FPSQ [2]	12.0022	0.9396	0.1449	0.2244	0.1805	3.3693
Proposed	9.2943	0.9627	0.1599	0.2610	0.2121	3.5797

Table 4.10 shows that the proposed algorithm performs better in terms of spectral quality and fusion quality. Spectral quality is evaluated through ERGAS and CC techniques and fusion quality is evaluated through Wavelet, Pixel, Gradient and MI methods.

Conclusion and Perspectives

5.1 Conclusion

A novel compressive sensing based filter approach for pan-sharpening has been proposed in this research. In traditional satellite image fusion techniques, the final fused images have been suffering from spectral distortion. In satellite image fusion, the colors of multispectral image should not change in the final fused image but most of the traditional satellite image fusion techniques compromise on this aspect while more focusing on the spatial quality [2]. Filter based image fusion technique has overcome on this drawback [2]. In proposed methodology, an optimized filter is used for image fusion. Regression coefficients are calculated by using the compressive sensing values of multispectral and panchromatic images. Optimal filter is constructed from input images and regression coefficients. Low resolution panchromatic image is generated from input panchromatic image and optimal filter. Low resolution panchromatic image reduces the spatial quality of input panchromatic image and construct optimal panchromatic values [2]. An optimal function for low resolution panchromatic image is constructed for injecting the optimal values of panchromatic image into the multispectral image. The optimal filter based approach of proposed technique preserves the spatial and the spectral qualities of the panchromatic and the multispectral images in the final fused image. In proposed technique, the colors of final fused image are visually similar to the colors of input multispectral image. The spectral quality of the fused images has been measured quantitatively [70]. Filter based image fusion also does not compromise on fusion quality. Proposed technique has been evaluated in terms of fusion quality. To verify the spatial and spectral aspects of the final fused image, the fusion quality is computed through different feature extraction methods [69] and MI [68]. Proposed method is supported by comparing with four state-of-the-art image fusion methods in both the spectral and the spatial domains of the fusion quality. All image fusion methods and proposed method fuse the same datasets. The visual assessment shows that the proposed method and fusion preserving spectral quality method have better results than other image fusion methods in terms of the spatial and the spectral qualities. In addition to the visual examination, the spectral and the spatial qualities were analyzed through quantitative measures. The quantitative analysis for spectral quality was performed with ERGAS and CC [70] and spatial quality was evaluated through Pixel, Wavelet and Gradient based feature extraction methods [69] and MI technique [68]. All spectral and spatial quantitative measurements demonstrate that the proposed method has improved the spatial and the spectral qualities in the final fused image. It also reduces the spectral distortion as compared to the peer fusion algorithms.

Previously proposed methodologies, such as component substitution techniques focus on spatial quality [2]. Filter based methodologies more focus on the spectral quality of the fused image [2]. But proposed technique shows the promising results in the field of satellite image fusion by focusing on both the spectral quality and the fusion quality of the fused image. Fused image must retain the spectral quality of the multispectral image and should not compromise on fusion quality. Proposed technique has much better results in terms of the spatial and the spectral qualities as compared to the other component substitution techniques and filter based techniques.

5.2 Future Perspectives

Development of a satellite image fusion technique is a very challenging task because very minute details are needed to preserved in the final fused image. This research endeavored to point out some of the issues facing by the satellite image fusion. The proposed method has achieved very decent results in the domain of spectral quality and fusion quality. The extension to suggested technique can be an optimal filter that can improve the spectral quality and fusion quality of the fused image. Compressive sensing is implemented in this technique to calculate the regression coefficients. Regression coefficients are used in the construction of optimal filter and low resolution panchromatic image. Compressive sensing values can be used in over-all fusion process. Low resolution panchromatic image construction process can be more optimal through which more spectral quality and fusion quality can be achieved in the fused image. In proposed technique, the fused image is constructed by injecting the low resolution panchromatic image into the multispectral image. For future work, more focus should be on construction of a low pass filter that can create an optimal low resolution panchromatic image to produce the better fusion results in the field of satellite image fusion.

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