SATELLITE IMAGE FUSION USING SSCSVR ALGORITHM WITH ADAPTIVE GAIN CONTROL ENHANCEMENT

PROJECT REPORT

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BONAFIDE CERTIFICATE

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT

Image Fusion refers to the task of combining two or more images into a single more informative image. The main aim of image fusion in the satellite images is to improve the information content of the available images for the purpose object detection, classification and land cover types. In this project, we focus on obtaining a pansharpened satellite image from Multispectral(MS) and Panchromatic(PAN) images using Synthetic Variable Ratio(SVR) with Spatial and Spectral Correlation(SSC). In the SVR based Component Substitution(CS) method, the spatial details are well injected into the fused image. The major drawback of CS method is the potential color distortion. In order to overcome the spectral distortion, local spectral and spatial correlation based SVR(SSCSVR) method is implemented. IKONOS and QuickBird satellite images are used to assess the quality of the method. The proposed approach of SSCSVR technique significantly improves the fusion quality and significantly reduces the spectral distortion. On further, the fused image is enhanced using the Adaptive Gain Control for the image detail preservation.

The performance measures that are used to quantify the performance of our framework are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

RGB	Red Green Blue
PAN	Panchromatic Image
MS	Multispectral Image
CS	Component Substitution
MRA	Multi-Resolution Analysis
SVR	Synthetic Variable Ratio
SSC	Spatial and Spectral Correlation
DWT	Discrete Wavelet Transform
IDWT	Inverse Discrete Wavelet Transform
GS	Gram-Schmidt Transform
IR	Image Registration
RS	Resampling
IHS	Intensity Hue Saturation
PCA	Principal Component Analysis
LP	Laplacian Pyramid
CVT	Curvelet Transform
MSE	Mean Square Error
PSNR	Peak Signal to Noise Ratio
SSIM	Structural Similarity Index Measure

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Optical remote sensing makes use of visible, near infrared and short-wave infrared sensors to form images of the earth's surface by detecting the solar radiation reflected from targets on the ground. Different materials reflect and absorb differently at different wavelengths. Thus, the targets can be differentiated by their spectral reflectance signatures in the remotely sensed images. Optical remote sensing systems are classified into the following types, depending on the number of spectral bands used in the imaging process.

Panchromatic imaging system

The sensor is a single channel detector sensitive to radiation within a broad wavelength range. If the wavelength range coincide with the visible range, then the resulting image resembles a "black-and-white" photograph taken from space. The physical quantity being measured is the apparent brightness of the targets. The spectral information or "colour" of the targets is lost. Images are collected in broad visual wavelength range. It provides high resolution of 10m pixel range. Examples of panchromatic imaging systems are:

- IKONOS PAN
- SPOT HRV-PAN

Multispectral imaging system

The sensor is a multichannel detector with a few spectral bands. Each channel is sensitive to radiation within a narrow wavelength band. The resulting image is a multilayer image which contains both the brightness and spectral (colour) information of the targets being observed. Each individual image is usually of the same physical area and scale but of a different spectral band. Examples of multispectral systems are:

- LANDSAT MSS
- LANDSAT TM
- SPOT HRV-XS

1.2 Image Fusion

Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images.

One of the most important terms to understand in image fusion is the word resolution which judges the quality of various fused images. Image resolution is defined as the smallest measurable detail in visual presentation or it is the amount of detail that an image holds. In satellite image fusion processing the term resolution can be classified into different types.

- **Spatial or pixel resolution**

  Spatial resolution or pixel resolution refers to the spacing of pixels in an image and is measured with the set of two positive integer numbers, where the first number is the number of pixel columns (width) and the second is the number of pixel rows (height), for example as 640 by 480. Higher spatial resolution allows a clear perception of sharp details and subtle color transitions in an image.

- **Spectral resolution**

  This refers to the frequency or spectral resolving power of a sensor and is defined as the smallest resolvable wavelength difference by the sensor.

CHAPTER 2

LITERATURE SURVEY

Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images.

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. Image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. However, the standard image fusion techniques can distort the spectral information of the multispectral data while merging.

2.1 IMAGE FUSION ALGORITHMS

The objective of image fusion algorithms is to make full use of spatial and spectral information in the Panchromatic and Multispectral images respectively, in order to reduce the potential colour distortion and provide a clear image information

Panchromatic images - Images collected in the broad visual wavelength range but rendered in black and white.

Multispectral images - Images optically acquired in more than one spectral or wavelength interval. Each individual image is usually of the same physical area and scale but of a different spectral band

2.1.1 Standard Image Fusion Methods

Image fusion methods can be broadly classified into two groups

- Spatial domain fusion
- Transform domain fusion

Spatial Domain Fusion Techniques

- Intensity Hue Saturation(IHS)
- Principal Component Analysis(PCA)
- Gram-Schimdt Context Adaptive Sharpening(GSA-CA)
- Synthetic Variable Ratio(SVR)
- Brovey Method
- Averaging

Transform Domain Fusion Techniques

- Wavelet Transform
- Laplacian Pyramid
- Curvelet Transform

2.2 Spatial Domain Image Fusion Techniques

2.2.1 Generalised Intensity Hue Saturation(IHS)

The author Shih-Gu Huang in his paper [2] described that as the MS image is represented in RGB color space, we can separate the intensity (I) and color information, hue (H) and saturation (S), by IHS transform. The I component can be deemed as an image without color information. Because the I component resembles the PAN image, we match the histogram of the PAN image to the histogram of the I component. Then, the I component is replaced by the high-resolution PAN image before the inverse IHS transform is applied. The main steps, illustrated in Fig. 2.1, of the standard HIS fusion scheme are

(1) Perform image registration (IR) to PAN and MS, and resample MS.

(2) Convert MS from RGB space into IHS space.

(3) Match the histogram of PAN to the histogram of the I component.

(4) Replace the I component with PAN.

(5) Convert the fused MS back to RGB space.

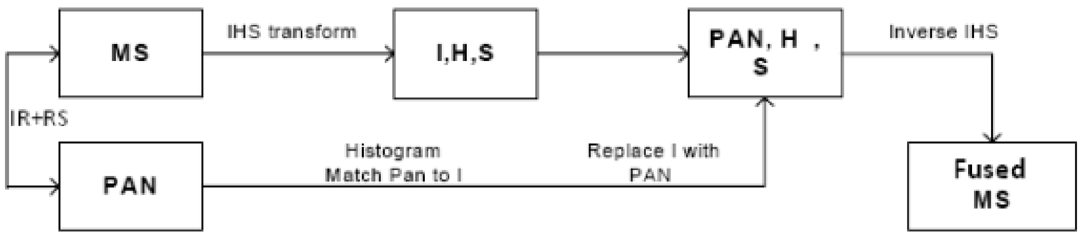

Fig 2.1 Generalised Intensity Hue Saturation

In step (1), image resampling is utilized so that the MS image has the same spatial resolution as the PAN image. IR and RS have introduced in Section 2. In step (3), because the mean and variance of the I component (I=(R+G+B)/3) are different to those of the PAN image, histogram matching is employed to prevent the change of the histogram of the MS image.

2.2.2 Principal Component Analysis(PCA)

An alternative to IHS-based method is principal component analysis (PCA). In Fig. 2.2, it is found out that the MS bands are somewhat correlated. The PCA transform can convert the correlated MS bands into a set of uncorrelated components, say PC1, PC2, PC3… The first principle component (PC1) also resembles the PAN image. Therefore, the PCA fusion scheme is similar to the IHS fusion scheme.

(1) Perform IR to PAN and MS, and resample MS.
(2) Convert the MS bands into PC1, PC2, PC3,… by PCA transform.
(3) Match the histogram of PAN to the histogram of PC1.
(4) Replace PC1 with PAN.
(5) Convert PAN, PC2, PC3, … back by reverse PCA.

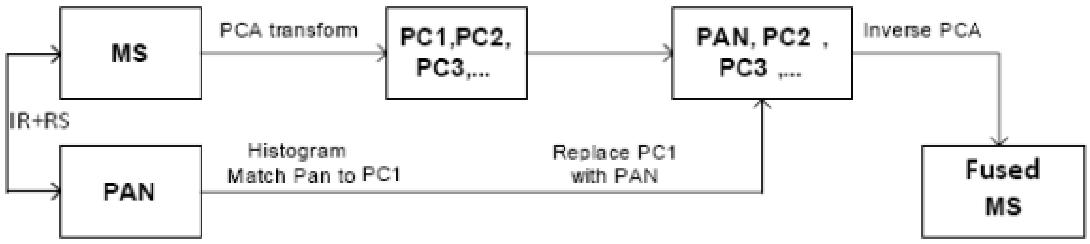

Fig 2.2: Principal Component Analysis

In general, the PC1 collects the spatial information which is common to all the bands, while PC2, PC3 … collect the spectral information that is specific to each band. Therefore, PCA based fusion is very suitable for merging the MS and PAN images. Compared to the IHS fusion,the PCA fusion has the advantage that the MS images is allowed to contain more than three bands. For instance, the near infrared component is also taken into account, or the MS image is form from more than one (satellite) sensors. In this case, the MS bands cannot be exactly separated into R, G and B bands.

2.2.3 Gram-Schimdt Context Adaptive Sharpening

In the paper [3],the author mentioned that the image fusion method utilizes Gram–Schmidt orthogonalization to enhance the spatial resolution of the MS image using the following steps:

(1) A lower spectral resolution PAN image (the same as the MS image) is derived by spatial averaging of 4*4 pixels of the original PAN image

(2) The modified Gram–Schmidt transformation is performed on the resulting PAN image together with the MS image.

The lower spatial resolution PAN image is used as the first band in the GS transformation.

(3) The statistics of the original PAN image are adjusted to match the statistics of the first transform band of the GS transformation.

(4) The statistically adjusted high resolution PAN image is substituted for the first transform band to produce a new set of bands.

(5) The inverse GS transformation is performed on the new set of bands to produce the pansharpened MS image.

2.2.4 Synthetic Variable Ratio

In the paper [4],the author used SVR technique which is based on multiple linear regression of a block (*i.e.*, a square region of pixels) to fuse the images. Multiplying the ratio of the original and synthesized PAN images, which is derived by multiple regression of the PAN image by MS bands, gives the pansharpened MS bands. Whereas the original SVR performs multiple regressions on an image basis, i.e., all pixels of the image are used to derive a single set of coefficients, it is modified to block-based regression here.

The processing steps are as follows:

(1) The low-resolution MS image is resampled (expanded) to the same size as the PAN image.

(2) Central and neighboring blocks (in total, N*N blocks) fetched from the MS and PAN images in sequence.

(3) Multiple linear parameters are calculated through multiple linear regression of the pixels in the blocks.

(4) The pixels in the central block are pansharpened using the SVR scheme and the calculated parameters(*i.e.*, regression coefficients).

(5) Steps (2) to (4) are repeated for all blocks.

2.2.5 Brovey Transform

In the paper of Comparison of Nine Fusion Techniques [7],the author described about the basic procedure of the Brovey Transform.It first multiplies each MS band by the high-resolution PAN band,and then divides each product by the sum of the MS bands.The Brovey Transform was developed to visually increase contrast in the low and high ends of an images histogram(i.e., to provide contrast in shadows, water, and high reflectance areas such as urban features). Consequently, the Brovey Transform should not be used if preserving the original scene radiometry is important. However, it is good for producing RGB images with a higher degree of contrast in the low and high ends of the image histogram and for producing “visually appealing” images. Since the Brovey Transform is intended to produce RGB images, only three bands at a time should be merged from the input multispectral scene.

The key advantages of the Spatial domain techniques are the Spatial details are well injected into the fused product and the computations are less difficult than transform domain techniques. The major disadvantage is that the spectral distortion of the image.

2.3 Transform Domain Image Fusion Techniques

2.3.1 Wavelet Transform

In the paper [2] of Wavelet for Image Fusion,the author stated that the standard IHS and PCA based fusion methods is suitable for the case that the I component (or PC1) of the MS image is highly correlated with the PAN image. This is possible only if the PAN band covers all the MS bands, and also if both the I component (or PC1) of the MS image and the PAN image has similar spectral response. The second condition is usually impossible. Thus, the two standard fusion methods usually introduce spectral distortion. The one-level DWT can decompose an image into a set of low-resolution sub-images (DWT coefficients), LL, H1, H2 and H3. The LL sub-image is the approximation image while the H1, H2 and H3 sub-images contains the details of the image. It is straightforward to have the fusion method to retain the LL sub-image of the MS image and replace the H1, H2 and H3 by those of the PAN image. Therefore, the fused image contains the extra spatial details from the high resolution PAN image. Also, if we downsample the fused image, the low-resolution fused image will be approximately equivalent to the original low-resolution MS image. That is, the DWT fusion method may outperform the standard fusion methods in terms of minimizing the spectral distortion. The main steps are

(1) Perform IR to PAN and MSi, and resample MSi.

(2) Match the histogram of PAN to the histogram of MSi.

(3) Apply DWT to both the histogram-matched PAN and MSi.

(4) Replace the detail sub-images (H1, H2 and H3) of MSi with those of PAN.

(5) Perform IDWT on the new combined set of sub-images.

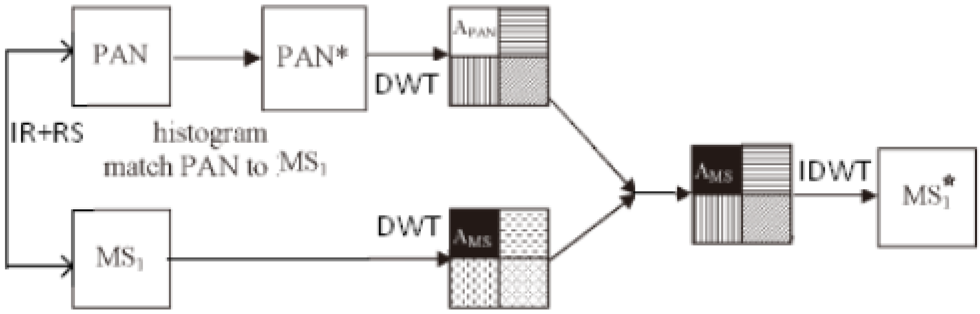

Fig 2.3: Wavelet Transform

2.3.2 Laplacian Pyramid

From the paper [5], it can be seen that the purpose of Laplacian decomposition is to decompose the original image into different spatial frequency bands, and to the different decomposition layers with different spatial resolutions, it can effectively merge the characteristics or details of the different images together by using different operators. It can get the visual effect close to peoples' vision characteristics finally.

The basic steps of image fusion based on Laplacian Pyramid transform are as follows. Here, we only take the fusion of two source images as an example, though it can be extended to handle mere than two images straight forwardly. Suppose A and B are original images of registration, F is the fused image.

(1) To perform Laplacian pyramid decomposition for the images to be fused separately and establish Laplacian pyramid for each image.

(2) To fuse the image pyramid layers decomposed separately, different layers can be used to mix with different fusion operators, the Laplacian pyramid of fused image can be obtained ultimately.

(3) To perform pyramid inverse transform on the new fused Laplacian pyramid, the reconstructed image will be fused image.

In this approach, we can obtain an optimum fused image which has richer information in the spatial domain.Fig.2.3 gives an overview of the organization of the algorithm

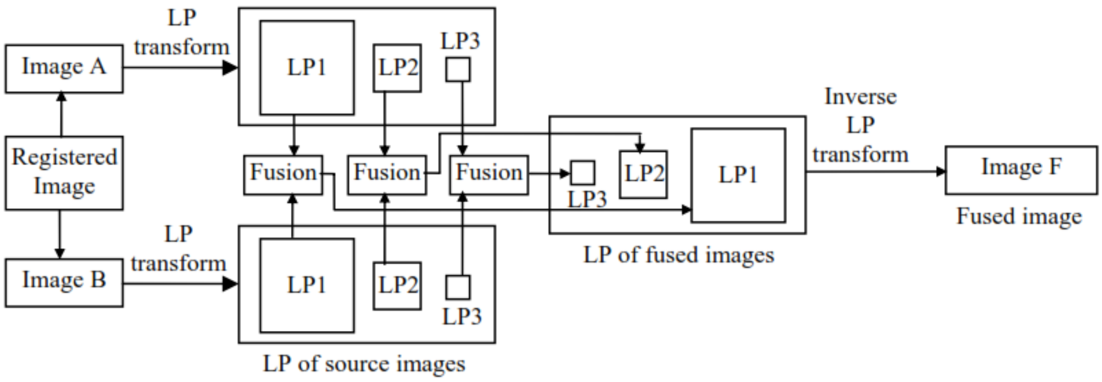

Fig 2.4: Laplacian Pyramid

2.3.3 Curvelet Transform

In the paper [6],the Curvelet transform (CVT) is described as a multi-scale transform proposed by Candes and Donoho and is derived from the Ridgelet transform. The Curvelet transform is suited for objects which are smooth away from discontinuities across curves. Fourier Transform does not handle point's discontinuities well because a discontinuity point affects all the Fourier Coefficients in the domain. Moreover, Wavelet transform handles point discontinuities well and doesn't handle curve discontinuities well. Curvelet transform handles curve discontinuities well as they are designed to handle curves using only a small number of coefficients.

The algorithm is as:

(1) The original pan and multispectral images are geometrically registered to each other.

(2) Three new pan images $I_{1,}I_2$,and I_3 are produced, whose histograms are specified according to the histograms of the multi-spectral images R, G, and B, respectively.

(3) By using well-known wavelet-based image fusion method, we obtained fused images I_1+R, I_2+G and I_3 +B respectively.

(4) I_1,I_2 and I_3 are decomposed into J+1 subbands, respectively, by applying "a trous" subband filtering..Each decomposed images include c_j which is a coarse or smooth version of the original image

(5) Each c_j is replaced by fused image which obtained from (3).

(6) The ridgelet transform is then applied to each block.

(7) Curvelet coefficients (or ridgelet coefficients) are modified in order to enhance edges in the fused image.
(8) The Curvelet reconstructions are carried out for I_1, I_2 ,and I_3 respectively. Three new images (F_1, F_2 ,and F_3) are then obtained, which reflect the spectral information of the original multi-spectral images R, G, and B, and also the spatial information of the pan image.
(9) F_1, F_2 ,and F_3 are combined into a single fused image F .

A. Subband Filtering

The purpose of this step is to decompose the image into additive components; each of which is a Subband of that image. This step isolates the different frequency components of the image into different planes without down sampling as in the traditional wavelet transform.

B. Tilting

Tiling is the process by which the image is divided into overlapping tiles. These tiles are small in dimensions to transform curved lines into small straight lines in the subbands P1 and P2. The tiling improves the ability of the curvelet transform to handle curved edges.

C. Ridgelet Transform

The ridgelet transform belongs to the family of discrete transforms employing basis functions. To facilitate its mathematical representation, it can be viewed as a wavelet analysis in the Radon domain. The Radon transform itself is a tool of shape detection. So, the ridgelet transform is primarily a tool of ridge detection or shape detection of the objects in an image.

The advantage of the above transform domain techniques is that the spectral information are maintained in the fused image and it holds good for classification process and further applications. However due to large number of computations, it consumes much power.

CHAPTER 3

ALGORITHM

3.1 INTRODUCTION

Over the past several years, the spatial domain transform has gained widespread acceptance in image processing in general and in satellite image fusion research in particular. In applications such as visual interpretation, land cover classification and change detection, the spatial and spectral correlation are used and for developing better schemes for image fusion. The Synthetic Variable Ratio is one of the spatial transform(CS) that makes the spatial details well injected into the fused image. The combinations of the spectral properties (observation wavelength and width of spectral bands) of multispectral and panchromatic images affect both the spatial and spectral quality of pansharpened images. Therefore, the clarification of the relations between spectral bands and quality of pansharpened image is important for improving our understanding of pansharpening methods. Thus the component substitution(CS) and multiresolution analysis(MRA) are used.

Earth observation satellites, such as Landsat-7,Spot 5, IKONOS, QuickBird, GeoEye-1, and WorldView-2 provide both panchromatic (PAN) images with high spatial resolution but low spectral resolution and multispectral (MS) images with high spectral resolution but low spatial resolution. QuickBird satellite data provide the PAN band at 0.7-m resolution and the MS image at 2.8-m resolution. To make full use of the spatial and spectral information, image fusion techniques have been applied in various remote sensing applications, such as image classification, object detection, and forest-type mapping. As the representative fusion method of the CS technique, the SVR techniques have clear physical meaning and theoretical basis, particularly the modified SVR fusion method. However, it was found that the spatial enhancement or spectral preservation of the fused image may not be occasionally satisfactory.

According to the analysis of SVR methods, it can be shown that an important drawback of the considered SVR methods is the direct use of the high-resolution PAN for the regression of the coefficients, which are utilized for determining the synthetic PAN. However, in this case, the calculation of the coefficients could be undermined by the decoupling between the high spatial frequencies present in the PAN images and absent in the MS images.

Solution of spectral and spatial correlation (SSC)-based synthetic variable ratio (SSCSVR) to remove the spectral distortion of fused image while preserving the spatial characteristic of the PAN image. First, the regression model of the SVR is improved with a spatial correlated component. Second, we adopted a modified localized adaptive processing strategy to better preserve the spectral information.

3.2 SYNTHETIC VARIABLE RATIO

In the SVR method, MS images and a high-resolution PAN image are merged. The low-resolution synthetic PAN image can be created from low-resolution MS bands whose spectral response overlap the one of the input high-resolution PAN band. The principle is as follows:

$$\mathrm{Pan}_{\mathrm{Syn}} = \sum \varphi_i \mathrm{MS}_i$$

where $\mathrm{Pan}_{\mathrm{Syn}}$ is the low-resolution synthetic PAN band, MS is the ith band of the MS image to be fused, and ϕ is the weight of the ith band of the MS image.

The SVR method supposes that the gray value ratio between the high-resolution PAN band and the low resolution $\mathrm{Pan}_{\mathrm{syn}}$ band reflects the spatial detail difference between the PAN and MS images. If these differences are distributed to every MS band by proportion, a high-resolution MS image can be reproduced, whose spatial resolution is the same as the PAN image

$$\mathrm{Fused}_i = \mathrm{MS}_i \times \frac{\mathrm{Pan}_{\mathrm{ori}}}{\mathrm{Pan}_{\mathrm{Syn}}}$$

where $\mathrm{Pan}_{\mathrm{ori}}$ is the high-resolution PAN image to be fused, and Fused_i is the ith band of fused MS image.

In the image fusion, the spectral preserving correlates with the interband structure of the MS image, and the spatial preserving correlates with the injection of the spatial structure from the PAN image. The traditional fusion method such as SVR only uses the spectral correlation between the PAN and MS images to build the multiple-linear-regression model. However, the pixels in an image are spatially correlated, meaning that, for a source image, if one pixel contributes to the fused image, its neighbors are likely to contribute to the fused image as well. Therefore, the decision making during the fusion process should exploit the property of spatial correlation.

In addition, the wavelength of the PAN image is relatively wide, thus the information in the PAN image not only contains the spectral characteristics of the MS bands but also contains more spatial details than the MS bands. Based on the aforementioned reasons, we build a more appropriate regression model to calculate weight ϕ_i, including both the SSC fraction. The improved SSC model is

$$\mathrm{Pan}_{\mathrm{ori}} = \sum \varphi_i \mathrm{MS}_i + \beta G_s$$

where ß is the weight of the spatial correlation fraction, and G_s is the spatial correlation fraction, i.e., high frequency information. In order to get the high-frequency G_s, we adopt the Gaussian filter method. $\otimes$ denotes the convolution, and Pan_L denotes the low frequency of the PAN image. Here, we employ the standard normal distribution is 1. The expression is as,

$$\mathrm{Pan}_L = G(x, y; \sigma) \otimes \mathrm{Pan}_{\mathrm{ori}}; \quad G_s = \mathrm{Pan}_{\mathrm{ori}} - \mathrm{Pan}_L.$$

The strategy of directly using the high-resolution PAN can keep well spatial details but bad spectral preserving, while the strategy of directly considering the low-resolution PAN is in contrast. Despite, we can see that the proposed approach is practically a tradeoff between the two strategies of considering the high and low resolution PAN images in computing the coefficients. ß is not a fixed value but an adaptive value that is the same as the other coefficients, could be obtained. If ß is 1, the strategy of considering the low-resolution PAN image is adopted, whereas if ß is 0, the strategy of using high-resolution PAN is considered.

Traditional SVR fusion methods use the global information to calculate the weight coefficients and do not take the local information into account. Local treatment has shown the greater advantage than the global processing in spectral information preserving. SSCSVR method adopts a blockwise computation to reduce the computational cost. The block strategy can make full use of the local feature.

CHAPTER 4

ADAPTIVE GAIN CONTROL

4.1 INTRODUCTION

Realistic display of high dynamic range images without introducing any artifact is a hard problem. In our approach, we address this problem using a detail preserving local gain control approach. Unlike many other local gain control methods available in the literature, our method is simple, and does not introduce ugly “halo” artifacts around the high dynamic range edges. We demonstrate the usefulness of this method by showing several examples.

The multispectral and panchromatic images that we perceived normally consist of light reflected from object surfaces. This reflected light depends on the amount of light incident on the surface and on the reflectance of the surface. In general, variation in the incident illumination is slow. Hence, the change in the perceived light intensity is mostly due to the change in surface reflectance values. Though the reflectance change at the junction of dissimilar objects can lead to significant intensity change (say, 20:1 in the case of printed black letters on a white page), average changes are much less in magnitude. Such approximation regarding the visual world breaks down in situations where both lighted and shadowed areas are visible, or the light source is present in the visual field. The intensity changes across the shadow edges, or across the edge of the light source surface can be very high (> 100:1). This high intensity change coupled with variations in reflectance gives rise to high dynamic range scenes with illumination range of more than 1000:1.

Unfortunately, dynamic range of image display devices and image display mediums are slow in catching up with the progress in digital image capture devices and methods. The dynamic range available for image display is between only one and two orders of magnitude. Simple scaling to fit the high dynamic range image data to the range of the available displays results in loss of image detail (local contrast) in bright areas and in dark areas. The detail in darker areas become indistinguishable from black and detail in brighter areas become indistinguishable from white. In our gain control approach, we present a very simple method for accurately displaying the fused images without any artifact. Using a local adaptation algorithm our method compresses high intensity changes while preserving intensity changes due to the change in surface reflectance with minimal compression. We detect the presence of high contrast edges and remove the influence of intensities present across the high contrast edge from the gain control.

There were several algorithms used priorly for displaying the high dynamic range images with enhancement. Though individual display algorithms differ from each other in detail, a typical algorithm operates by deriving a scale factor (gain) dependent on the scene ambient illumination and then by multiplying (gain control) this scale factor with each pixel to produce the display pixel value. The resulting image preserves the relative changes in intensity due to the change in reflectance. However, such uniform scaling approach does not work for high dynamic range scenes. The main reason of this failure is: A single ambient is not representative of the whole scene. The visual system adapts locally to the prevailing illumination condition [Patt98] and this illumination condition is likely to be very different from region to region in a high dynamic range scene.

The another method for enhancement used is the weighted mean approach. In this method, the weight chosen varies as a function distance. While these methods are able to compress the dynamic range, they invariably introduce artifact (in the form of halos) around the high contrast edges (the boundaries which separate bright areas from dark areas). The halos arise because on the dark side of the high contrast edge the local mean becomes significantly larger due to the influence of the bright neighbouring pixels. This large mean value underestimates the gain and hence the pixels after gain control look darker. Similarly, for the pixels on the brighter side of the high contrast edge, the local mean overestimates the gain, and thus makes the gain controlled pixels brighter than expected. The key to removing this problem is to remove the influence of extreme pixels values from the gain control process

4.2 ALGORITHM

The main goal of our method is to preserve detail in both lighted and dark areas. We achieve this goal by local gain control. For every pixel, gain is derived from a local ambient. The weighted mean of pixels in a local neighbourhood is used as this local ambient. Unlike many other methods already available, our weight function is independent of the position of the neighbouring pixels. But, it is dependent on the magnitude of the change in intensity of the neighbouring pixels from the pixel under consideration. The weight function is derived in the following paragraphs. To avoid the influence of extreme pixels at high intensity boundaries, we wish to use only those neighbouring pixels whose intensity variation from the pixel under consideration are within a factor of 5. We place a circular mask around every pixel (Intensity I_c) and compute the geometric mean of only those pixels (intensities I), which are within the circular mask and satisfy the following condition:

$$\begin{aligned} & \frac{1}{5} \le \frac{I}{I_c} \le 5 \\ or \quad & -1 \le \log_5(I) - \log_5(I_c) \le +1 \\ or \quad & \left|\log_5(I) - \log_5(I_c)\right| \le 1 \end{aligned} \qquad (1)$$

The value 5 was chosen based on the standard convention used in the field of photography, of white being 5 times as intense as mid grey and black being a little less than $1/5^{th}$ as intense as mid grey [Hunt95].

We use the mean intensity as the local ambient for the center pixel and compute its gain from any of the number of equations available in the literature [Ward94, Ferw96 or Patt00]. Choosing pixels for mean computation based on the condition defined in Equation 1 is equivalent to computing a weighted mean with the weight function defined in Equation 2.

$$weight(I) = \begin{cases} 1 & \text{if } \left|\log_5(I) - \log_5(I_c)\right| \le 1 \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

Use of such weighted mean as local ambient, will suffice for images with sharp boundaries. However, photographs of natural scenes tend to have boundaries with a slightly smoother profile. In order to accommodate for slightly smooth high intensity boundaries we choose a smoother form of Equation 2. The smooth function is given in Equation 3.

$$weight(I) = e^{-\left|\log_5(I) - \log_5(I_c)\right|^{25}} \qquad (3)$$

The value of 25 as the exponent in Equation 3 allows for a smooth but almost sharp drop off in the function from one to zero. Any value close to 25 may be equally acceptable.

The use of geometric mean instead of arithmetic mean as the local ambient has been suggested earlier by Tumblin *et al* [Tumb99]. We also believe that geometric mean helps in better preserving the relative ratios (local contrast) in the scene.

Algorithm for Adaptive Gain Control

```
[r,g,b] = LoadImage; % use your image loader
y = RGB_To_Luminance(r,g,b);
[rows,cols] = size(y);
%
logy = log(y)/log(5);
%
yAmbient = zeros(rows,cols);
%
for i = 1:rows
   for j = 1:cols
      % get pixels from a circular neighborhood
      cneighbor = CircularNeighbor
                        (logy,i,j,neighborRadius);
      diff = cneighbor-logy(i,j);
      fac = exp(-abs(diff).^25);
      % Compute Weighted geometric mean
      gMean = sum(diff.*fac)/sum(fac)
 % Arithmetic mean in log domain is same as geometric mean in linear domain.
      yAmbient(i,j)=exp((gMean+logy(i,j))*log(5));
   end;
end;
%
```

```
[r1,g1,b1]= GainControl(y, r, g, b, yAmbient) ;
%write out the display image.
tiffwrite(r1,g1,b1,outfile);
```

The above described algorithm has been used in the MATLAB in order to enhance the fused image using adaptive gain control.

CHAPTER 5

MATLAB

MATLAB (**mat**rix **lab**oratory) is a numerical computing environment and fourth-generation programming language. Developed by Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and FORTRAN. Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing capabilities. An additional package, Simulink, adds graphical multi-domain simulation and Model-Based Design for dynamic and embedded systems.

MATLAB Compiler compiles a MATLAB application into a standalone application or software component. The act of compiling this code is sometimes referred to as building. Building with MATLAB Compiler enables you to run your MATLAB application outside the MATLAB environment. It reduces application development time by eliminating the need to translate your code into a different language. If you are building a standalone application, MATLAB Compiler produces an executable for your end users. If you integrate into C or C++, MATLAB Compiler provides an interface to use your code as a shared library. If you integrate into other development languages, MATLAB builder products (available separately) let you package your MATLAB applications as software components. You are able to use Java classes, .NET components, or Microsoft Excel add-ins. It provides good platform for performing image processing operations.

Image Processing Toolbox provides a comprehensive set of reference-standard algorithms and graphical tools for image processing, analysis, visualization, and algorithm development. You can perform image enhancement, image deblurring, feature detection, noise reduction, image segmentation, spatial transformations, and image registration. Many functions in the toolbox are multithreaded to take advantage of multicore and multiprocessor computers. Image Processing Toolbox supports a diverse set of image types, including high dynamic range, giga pixel resolution, ICC-compliant color, and tomographic images. Graphical tools let you explore an image, examine a region of pixels, adjust the contrast, create contours or histograms, and manipulate regions of interest (ROIs).

With the toolbox algorithms you can restore degraded images, detect and measure features, analyze shapes and textures, and adjust the color balance of images.

Key Features

- Image enhancement, filtering, and deblurring
- Image analysis, including segmentation, morphology, feature extraction, and measurement
- Spatial transformations and image registration
- Image transforms, including FFT, DCT, Radon, and fan-beam projection
- Workflows for processing, displaying, and navigating arbitrarily large images
- Modular interactive tools, including ROI selections, histograms, and distance measurements
- ICC color management
- Multidimensional image processing
- Image-sequence and video display
- DICOM import and export

MATLAB supports standard data and image formats, including JPEG, JPEG-2000, TIFF, PNG, HDF, HDF-EOS, FITS, Microsoft Excel, ASCII, and binary files. It also supports the multiband image formats BIP and BIL, as used by LANDSAT for example. Low-level I/O and memory mapping functions enable you to develop custom routines for working with any data format.

CHAPTER 6

SIMULATION RESULTS

5.1 INTRODUCTION

The results of SSCSVR based image fusion methods on various MS and PAN images are presented in this chapter. The performance measure that has been used to analyze the results are Mean Square Error (MSE), Peak Signal to Nose ratio (PSNR) and Structural Similarity index (SSIM) computation. The images were analyzed and processed in MATLAB for SSCSVR image fusion.

5.2 PERFORMANCE METRICS

The results are analyzed using different quantitative metrics which are detailed below:

- **Mean Square Error (MSE)**: Mean Square Error is the average squared difference between a reference image and reconstructed image. For a m x n reference image I and reconstructed image K, the MSE is given by:

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad (5.1)$$

  where i and j are the rows and columns of the image.

- **Peak Signal to Noise ratio**: Peak Signal to Noise Ratio is the ratio between the reference image and the reconstructed image, given in decibels. The higher the PSNR value, the closer the reconstructed image is to the reference image.

$$\mathrm{PSNR} = 10.\log_{10}\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}} \quad (5.2)$$

where MAX_I is the maximum possible pixel value of the image. MAX_I=255 for 8-bit images.

- **Structural Similarity Index (SSIM)**: The structural similarity (SSIM) index is a method for measuring the similarity between two images. It is calculated on various windows of an image. The measure between two windows x and y of common size $N \times N$ is:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (5.3)$$

where μ_x and μ_y are the average of x and y, σ_x^2 and σ_y^2 are the variance of x and y, σ_{xy} is the covariance of x and y, $c_1=(k_1L)^2$, $c_2=(k_2L)^2$ are the two variables to stabilize the division with weak denominator; L is the dynamic range of the pixel-values, $k_1=0.01$ and $k_2=0.03$ by default.

5.3 SIMULATION RESULTS

Test Image: QuickBird Satellite image

Input Images:

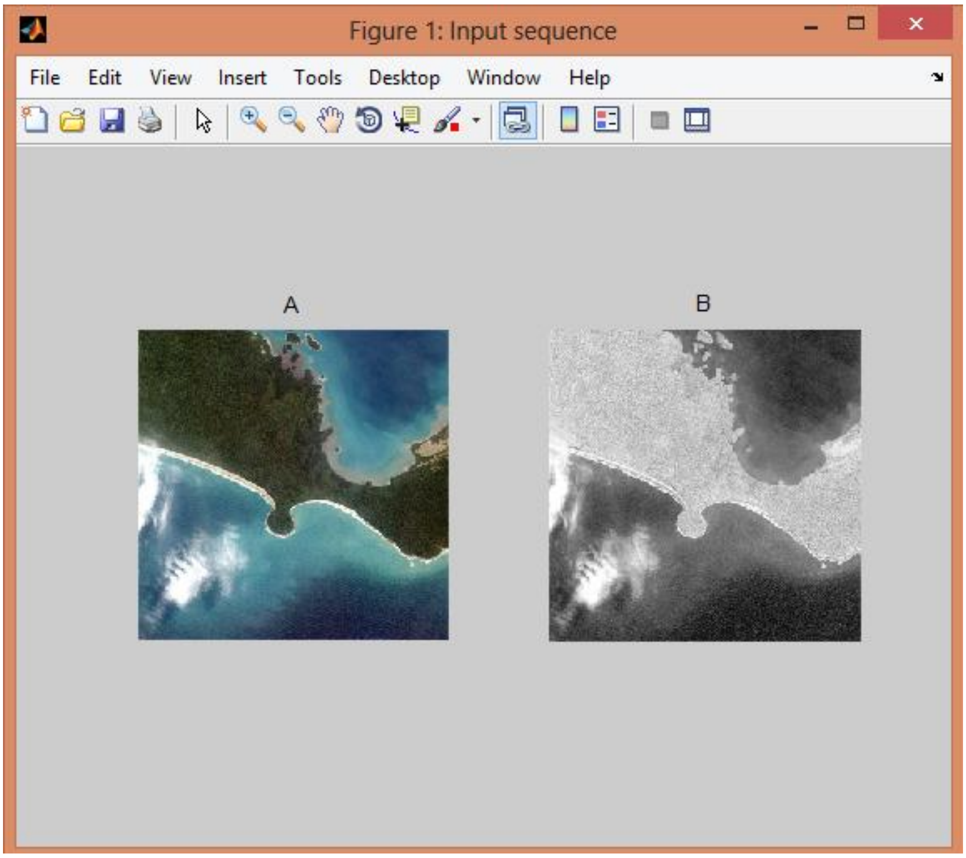

Fig 5.1 : (A) Multispectral Image (B) Panchromatic Image

Depth of Field:

Depth of field refers to the range of distance that appears acceptably sharp. It varies depending on camera type, aperture and focusing distance, although print size and viewing distance can also influence our perception of depth of field. The depth of field does not abruptly change from sharp to unsharp, but instead occurs as a gradual transition. In fact, everything immediately in front of or in back of the focusing distance begins to lose sharpness — even if this is not perceived by our eyes or by the resolution of the camera.

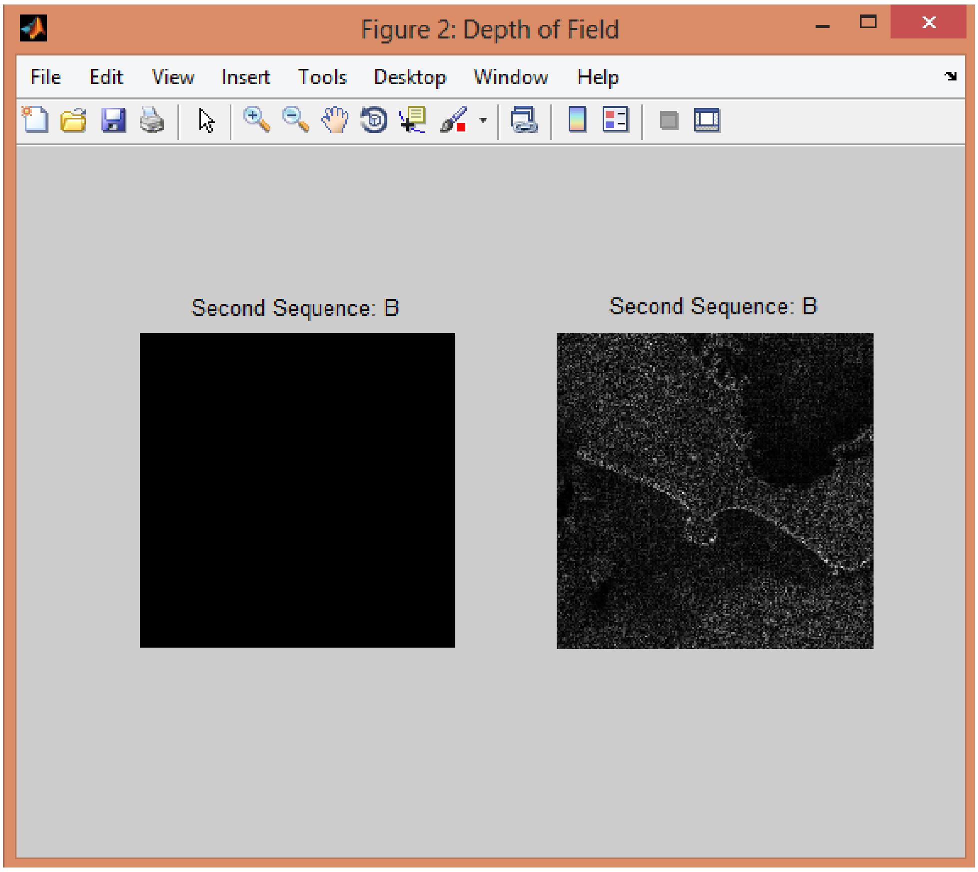

Fig 5.2: Depth of Field Measure of MS and PAN images

Gradient Measure:

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. The gradient of a two-variable function (here the image intensity function) at each image point is a 2D vector with the components given by the derivatives in the horizontal and vertical directions. At each image point, the gradient vector points in the direction of largest possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction.

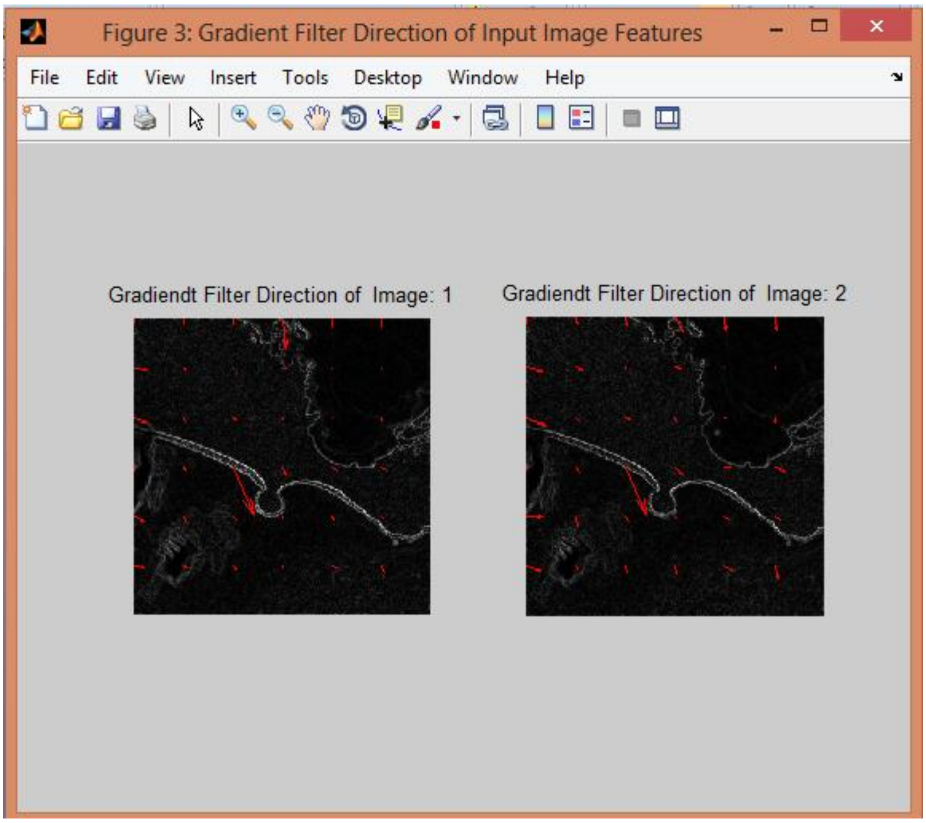

Fig 5.3: Gradient Measure for both input images

Contrast Measure:

Contrast is the separation of the lightest and darkest parts of an image. An increase in contrast will darken shadows and lighten highlights. Increasing contrast is generally used to make objects in an image more distinguishable.

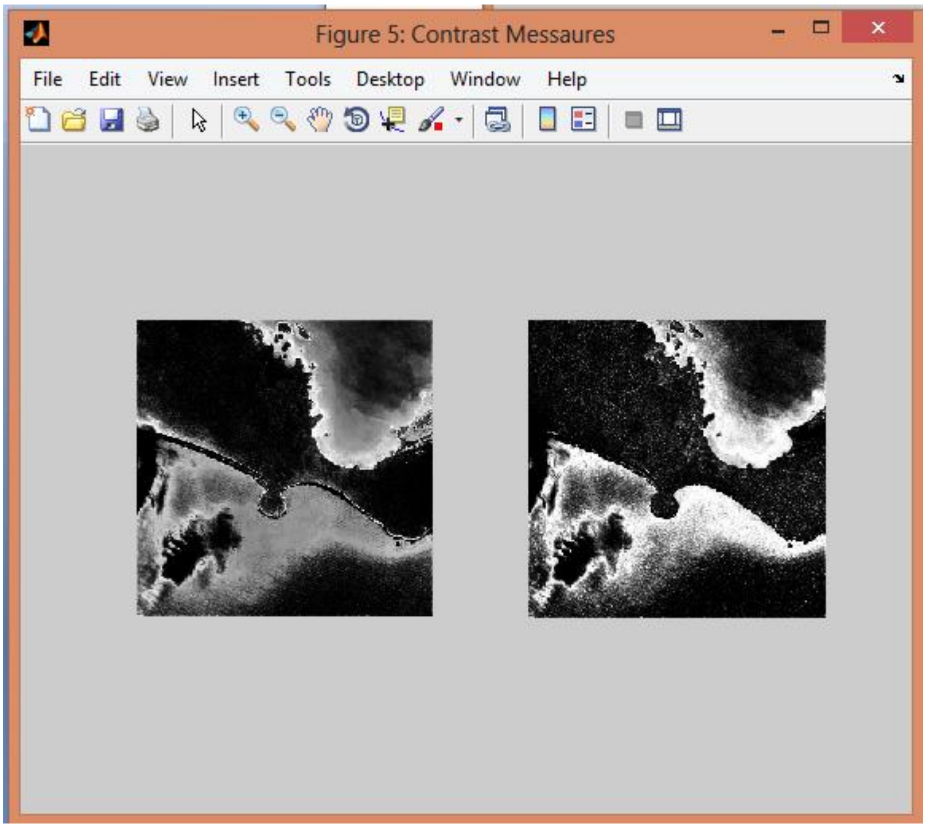

Fig 5.4: Contrast Measure for MS and PAN images

Image Pyramid:

An image pyramid is a collection of images - all arising from a single original image - that are successively downsampled until some desired stopping point is reached. There are two common kinds of image pyramids:

- **Gaussian pyramid:** Used to downsample images
- **Laplacian pyramid:** Used to reconstruct an upsampled image from an image lower in the pyramid (with less resolution)

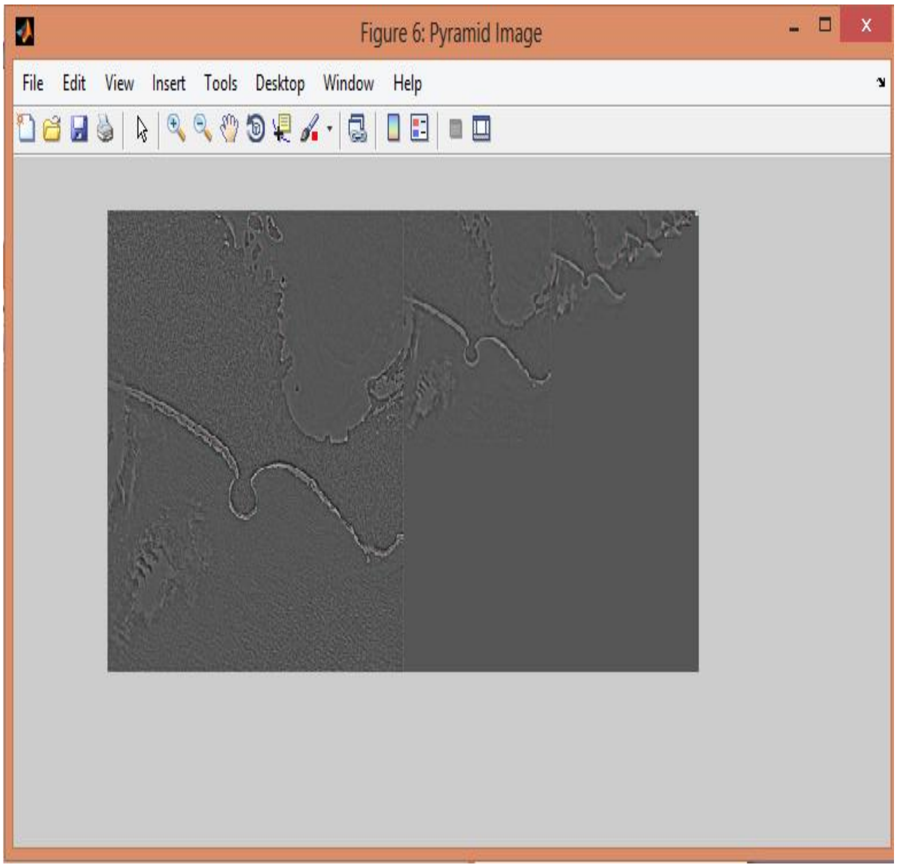

Fig 5.5: Pyramid Image Measure for input images

Normalised Image:

Normalization is a process that changes the range of pixel intensity values. Normalization is sometimes called contrast stretching or histogram stretching.

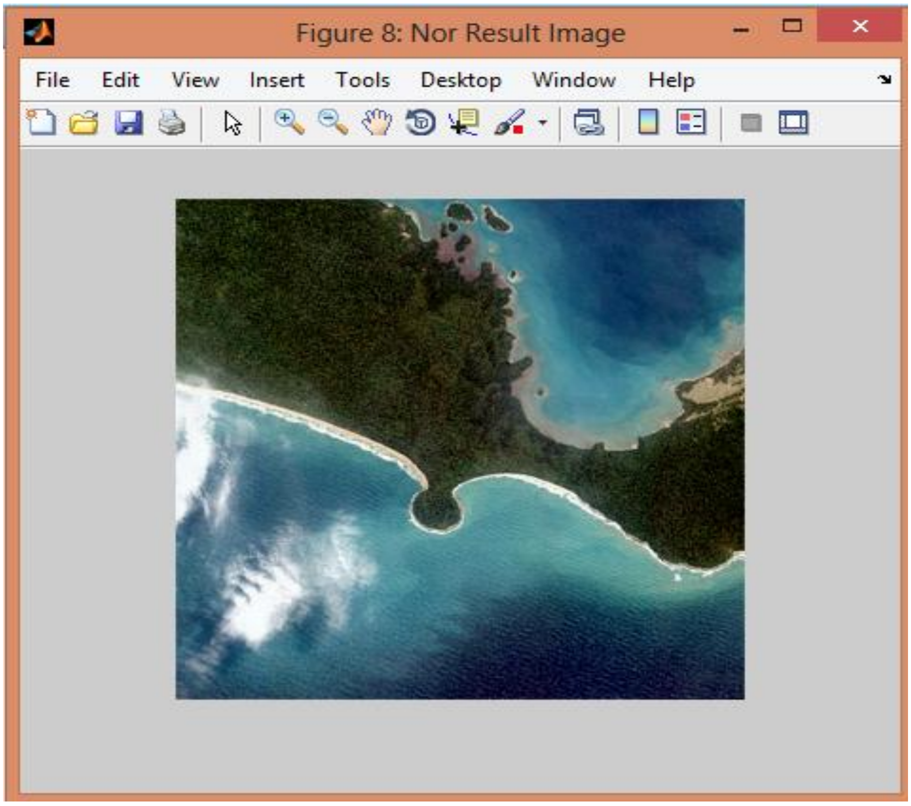

Fig 5.6: Normalised Fused Image

PSNR:

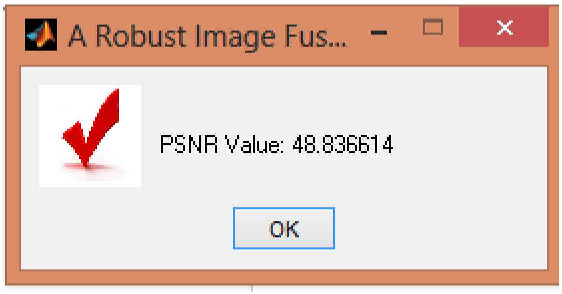

Fig 5.7: Peak Signal to Noise Ratio

SSIM:

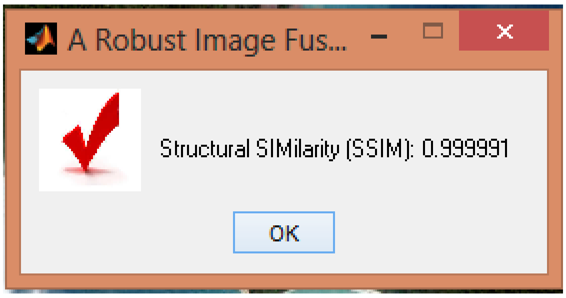

Fig 5.8: Structural Similarity Index Measure

Second Image

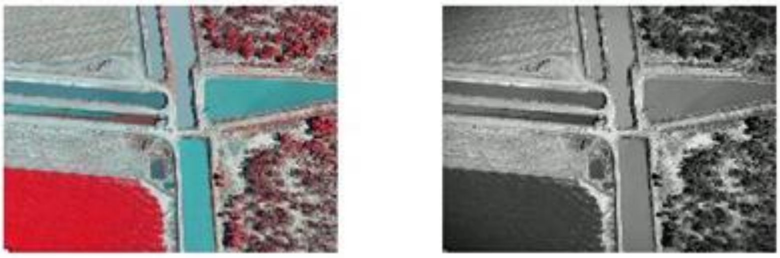

Fig 5.9: Multispectral and Panchromatic Images

Fig 5.10: SSCSVR Fused Image

PSNR and SSIM Metrics

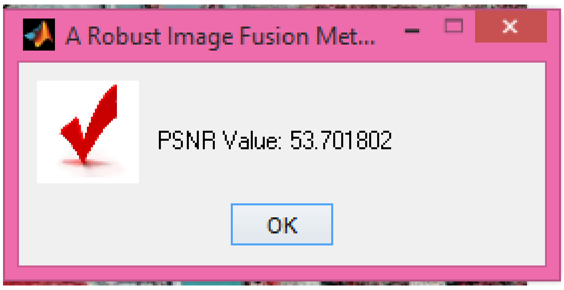

Fig 5.11: Peak Signal to Noise Ratio

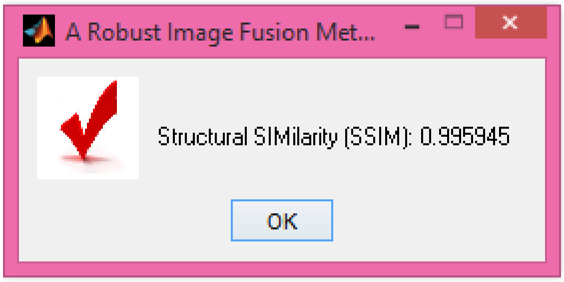

Fig 5.12: SSIM Calculation

Third Image

Fig 5.13: MS and PAN Images

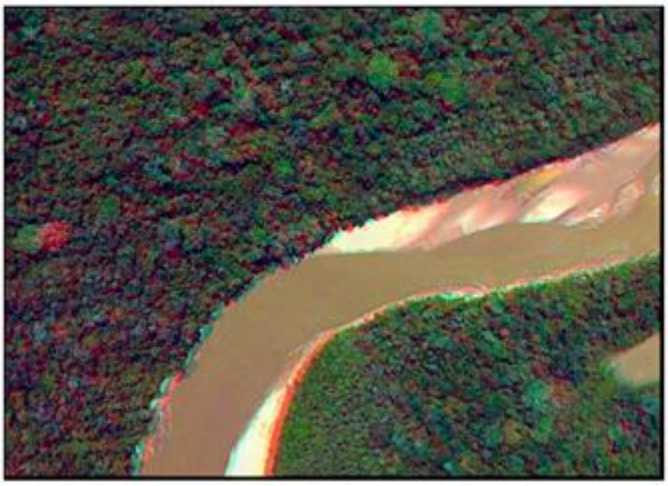

Fig 5.14: Fused Image using SSCSVR

5.4 ADAPTIVE GAIN CONTROL RESULTS

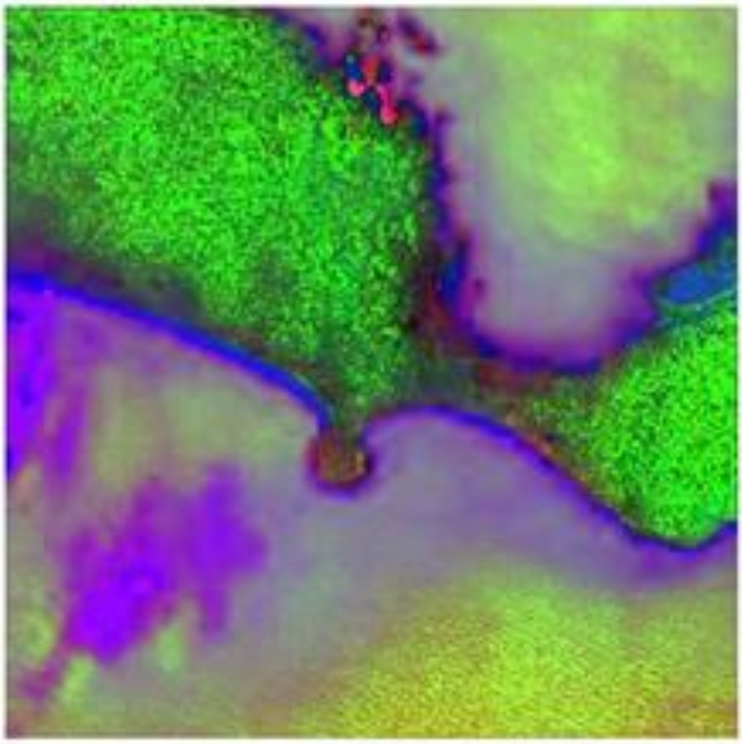

Fig 5.15: RGB to HSV Color Model (Image 1)

Fig 5.16: Fused Image and the enhanced image (Image 1)

PSNR of the enhanced image = 51.226

Second Image

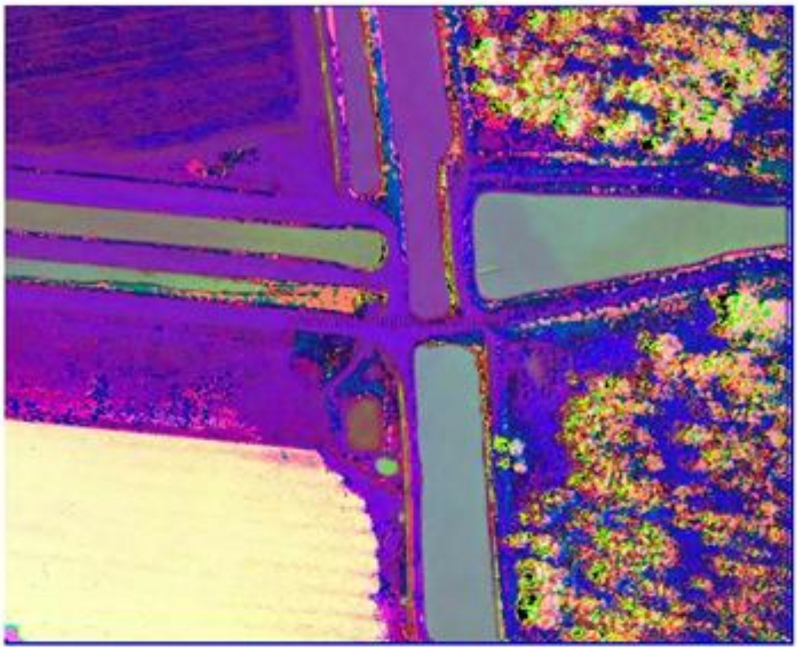

Fig 5.17: RGB to HSV Color Model (Image 2)

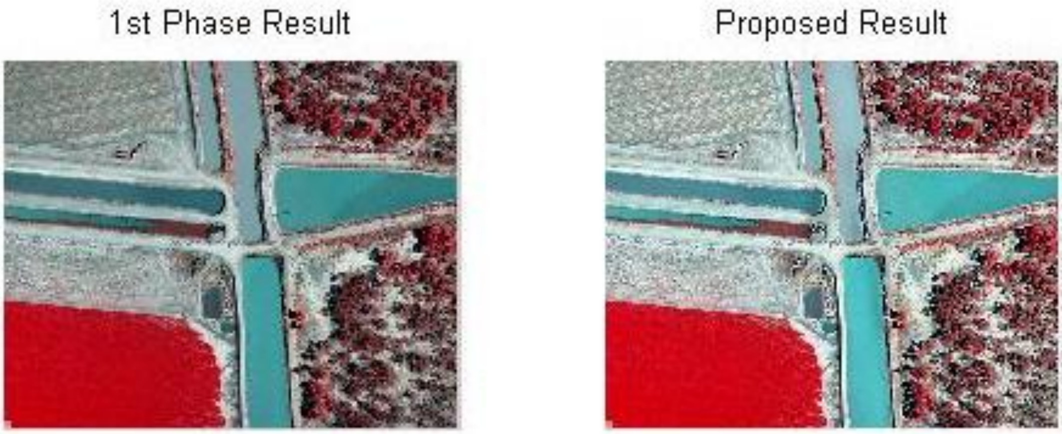

Fig 5.18: Fused Image and the enhanced image (Image 2)

PSNR of the enhanced image = 55.435

Third Image

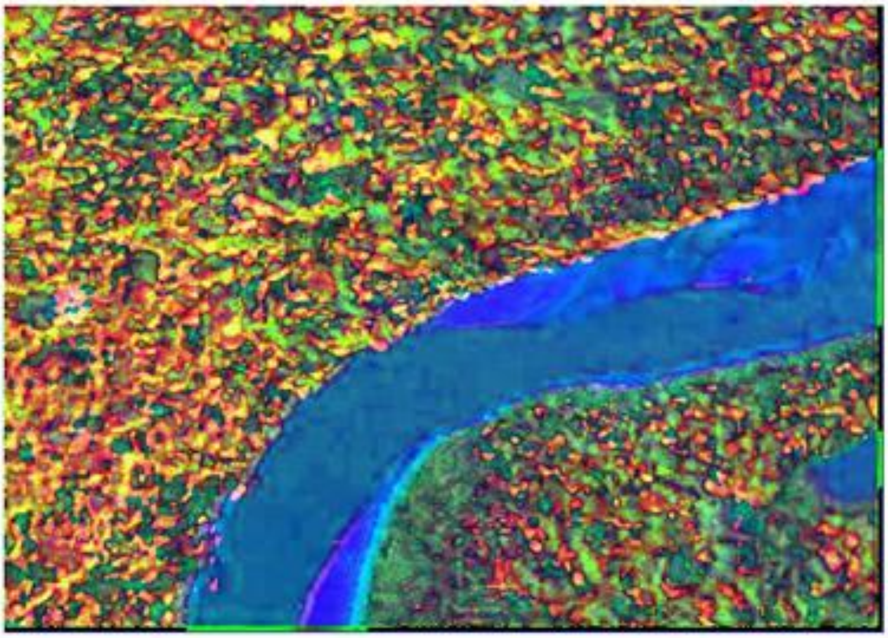

Fig 5.19: RGB to HSV Color Model (Image 3)

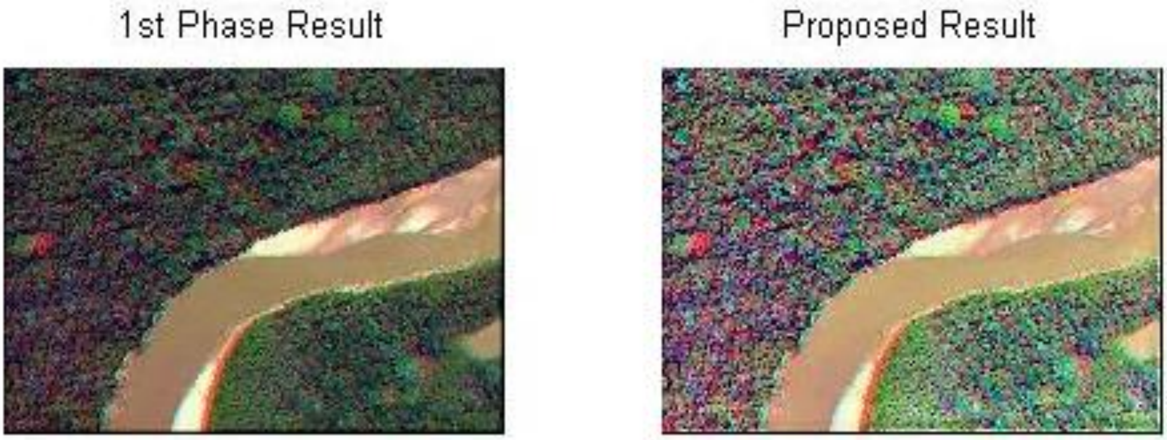

Fig 5.20: Fused Image and the enhanced image (Image 3)

PSNR of the enhanced image = 58.234

The above simulation results of the Multispectral and Panchromatic images were simulated using MATLAB 2013a. Initialy the image fusion technique was performed using SSCSVR algorithm and from the fused image result further enhancement was done using adaptive gain control mechanism.The Performance Metrics were also calculated for both the techniques and depicted above.

CHAPTER 7

CONCLUSION AND FUTURE WORK

The current work has provided a technique of obtaining a reduced spectral distorted pansharpened fused satellite image from multispectral and panchromatic images using spatial and spectral correlated synthetic variable ratio (SSCSVR) fusion technique. In the component substitution based image fusion method, the major spectral distortion is due to dissimilarities and aliasing of the multispectral and panchromatic images. Generally, the component substitution based SVR technique provides better spatial resolution. In image fusion technique, the main loss is in its high frequency components (i.e., edges), which is due to the smoothing caused by interpolation. In order to increase the quality of the fused image, preserving the edges is essential. Thus Laplacian Pyramid has been employed for enhancing the contrast of the image and thereby detected the depth of the field for image fusion. The resulting image is of higher visual quality than any of the input images.

The proposed SSCSVR technique produces good fusion results on a variety of images and there is a significant improvement in MSE, PSNR and SSIM. The fused image has been enhanced using Adaptive Gain Control method and thereby reduces the artifacts. The image details are preserved using this technique. This technique significantly improves the PSNR value of the fused image.

As a future work, the above image fusion technique can be simulated using ModelSim and will be implemented in the FPGA in order to estimate power and area factors.

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LIST OF PUBLICATIONS

Conference

- Presented a paper titled "Image Fusion Technique on Satellite Images with Reduced Spectral Distortion" in the IEEE sponsored 9th International Conference on Intelligent Systems and Control (ISCO'15) on 9th & 10th Jan,2015 held at Karpagam College of Engineering, Coimbatore.

Journal

- Published a paper in the title "Image Fusion Technique on Satellite Images with Reduced Spectral Distortion" in the International Journal of Applied Engineering Research(IJAER)- Annexure II (ISSN 0973-4562, Volume 10, Number 1 (2015) pp. 1045-1048)