Content Dependent Quality Measures for Image Fusion

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Abstract
Satellite images acquired form sensors exhibit either good spectral characteristics (multispectral data) or high spatial characteristics (panchromatic data) in remote sensing. Image fusion is imperative to enhance the interpretation quality of images. The quality evaluation of the decisive fused image is a difficult task in the realm of remote sensing, due to unavailability of a reference image general. An attempt through this study is made, to obtain the objective measurements using content based segmentation for evaluating the performance of the fused images. The spectral and spatial changes for each region and the signal to noise ratio between the original multispectral image and the fused image are used to assess the performance of the fusion technique. Most commonly used fusion techniques such as Principal component analysis, Multiplicative merge, Brovey transform and Lifting Wavelet transform are evaluated using the proposed approach. The results illustrate that the content based segmentation is objective and any priori information is not a requisite. The performance evaluation ascertains that Lifting Wavelet transform outperforms the other fusion techniques.

1. Introduction

Image fusion is a technique that merges the multispectral image that has high spectral resolution and low spatial resolution with panchromatic image having high spatial resolution and low spectral resolution. Ideally, the method used for image fusion should preserve the spectral characteristics of the original multi spectral input image. The fused image should have absolute information than multispectral image and panchromatic image. Image fusion is more expedient and economical than designing an advanced sensor with both resolution characteristics. Image fusion can be performed at three different levels in accordance with the phase at which fusion takes place at Pixel, Feature and Decision level (Pohl and Genderen, 1998). Pixel level fusion refers to the merging of physical parameter values measured by the sensor of the satellite. Feature level entail algorithms capable of recognizing objects in the various data sources, i.e. based on statistical characteristics of dimension, shape, edges etc. Segmentation procedures are constructive in this respect. The objective of the study is to segment the given multispectral image into individual regions and evaluate the quality of the various image fusion techniques.

1.1 Image Segmentation

The image segmentation aims at partitioning of the image into a set of regions which are visually distinct and uniform with respect to properties such as gray level, texture or colors (Gonzalez and Woods, 1992). Image segmentation is not only essential but also a critical component of any image analysis. The concept of region growing and merging algorithm to color was studied (Tremeau and Borel, 1997) and few region based algorithms were tested to compare their limits. Another approach for segmentation using recursive region splitting method (Ohlander et al., 1978) was on testing some histogram algorithms and their contribution to image segmentation**.** Efficient graph-Based Image Segmentation technique was reviewed and the problem of segmenting an image into regions is addressed (Pedro et al., 2004). The predicate was chosen for measuring the evidence for a boundary between two regions using a graph-based representation of the image. The SOM based image segmentation (Yuan et al., 2005) is used for segmenting images based on SOM neural network. At the outset, the pixels are clustered based on their color and spatial features, where the clustering process is accomplished with a SOM network. In new automatic image segmentation method (Jianping et al., 2001), the color edges in an image are first obtained automatically by combining an improved isotropic edge detector and a fast entropic threshold technique. Then the obtained color edges have provided the major geometric structures in an

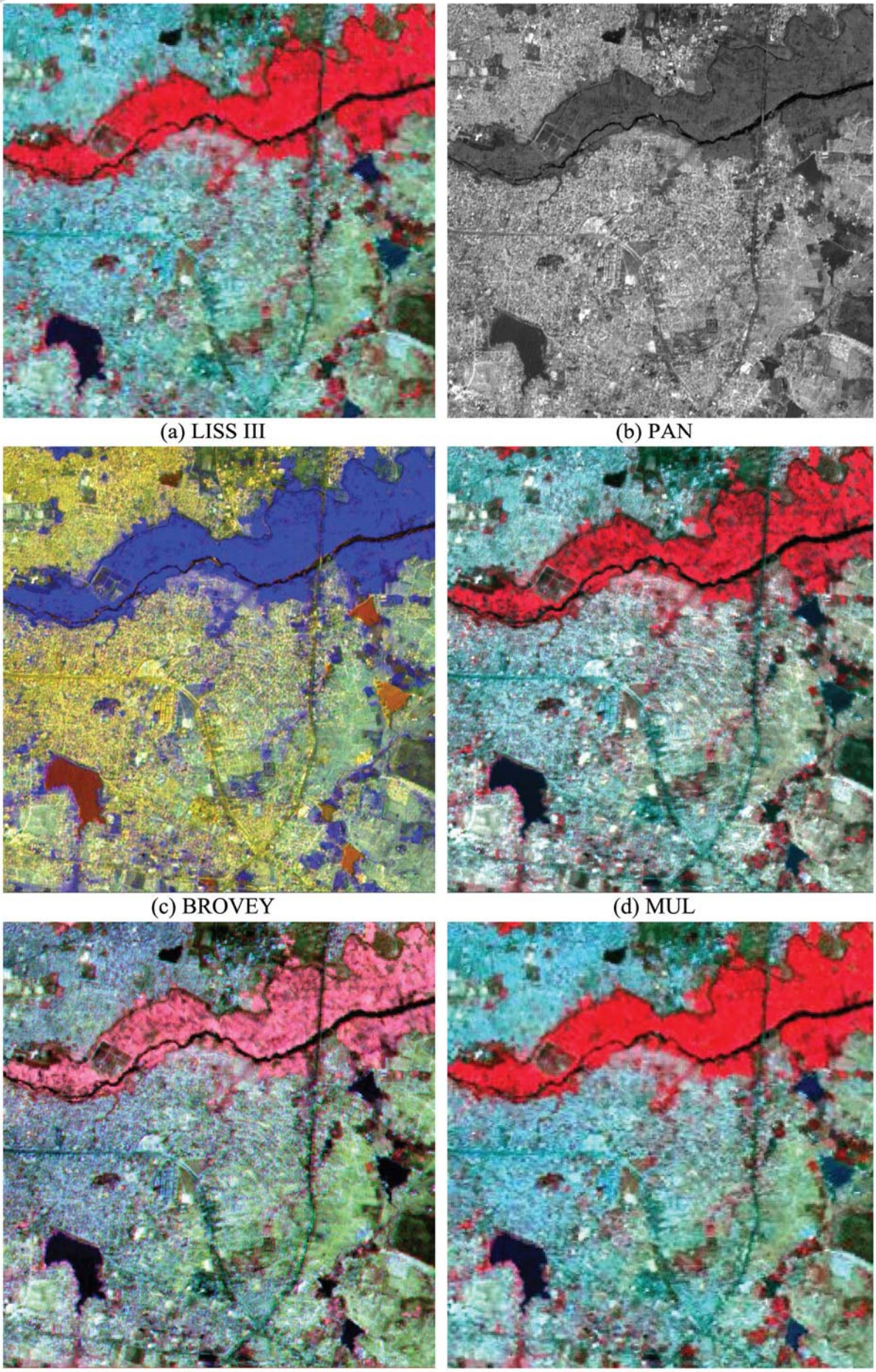
image. The problem of segmentation is still an important research field in spite of the methods proposed in the literature.

1.2 Quality Assessment

Quality refers to both the spatial and spectral quality of images. Image fusion methods aim at increasing the spatial resolution of the multispectral images while preserving their original spectral content. The spectral content is very important for photo interpretation and classification of objects. Consequently there is a rising demand for pertinent quality assessment tools to compare the results obtained from different fusion techniques and to obtain an optimal setting of parameters for a specific fusion technique (Wald et al., 1997). The assessment of image fusion is done by measuring the quantity of enhanced information in fused images using entropy and image noise index (Lau et al, 2001). Variance is used as quality parameter suggested measure based on local variance computed over a three-by-three pixel window (Beauchemin et al., 2002). The correlation coefficient between the high-pass filtered components of the fused and high-resolution panchromatic images is used as a quality index to evaluate the spatial quality of a merged image (Zhou et al., 1998). A spatial quality assessment approach is also based on the sensor's point spread function estimation (Li, 2000). Standard deviation of the difference between the input image and the fused image is taken as the performance measure of the fusion scheme (Li et al., 1994). Further methods utilize information theory metrics as mutual information (Qu et al., 2002) and entropy (Wang et al, 2003). A measure of fusion performance is developed by evaluating the amount of edge information transferred from input images to the fused image (Xydeas and Petrovic, 2000). The universal image quality index is used to construct a new fusion quality metric which does not require a reference image (Piella and Heijmans, 2003). Most of the developed assessment techniques are application specific. They do not take the particular objectives of the spectral preservation and non subjective edge enhancement of image fusion into consideration. Ramesh and Ranjith (2002) gave the concept of fusion symmetry as a measure of evaluating performance of fusion algorithms. An algorithm for image fusion using a lifting wavelet filter is proposed. Luo (2006) proposed a reliable automatic method for objective image quality measurement by noise analysis throughout the spatial frequency range with a fast lifting wavelet algorithm. The experimental results showed that image quality measurement exhibit good correlation to subjective visual quality assessments. Wang and Simoncelli (2005) proposed a reduced reference image quality assessment on a natural image statistic model in the wavelet transform domain. The proposed method is easy to implement and computationally efficient. Cvejic et al., (2005) presented a novel objective non reference performance assessment algorithm for image fusion. The experimental results confirm that the values of the proposed metrics correlate well with the subjective quality of the fused images. Objective performance assessment is a difficult issue due to the variety of different application requirements and the lack of a clearly defined ground-truth. From the literature review it has been concluded that the unsupervised segmentation techniques are not emphasized qualitatively and also there is a need for the assessment of fusion techniques, based on both spectral and spatial quality evaluation. Image segmentation and estimation of the fusion performance is still being an open problem, therefore, needs more attention from the scientific community. The proposed method utilizes a content-based approach, splitting the original image into different regions with various spatial characteristics and performs the fusion evaluation for each particular region independently. The measures are based on clear physical meanings, they are straightforward to implement and do not require any ground-truth.

2. Content Based Image Segmentation

The content dependent image segmentation technique is an unsupervised one which generates regions with same spatial characteristic. This technique uses the spatial variability in the image for region generation. This procedure partition an image into its constituent parts or objects. The goal of the fusion is to enhance the spatial resolution of the multispectral imagery while preserving the spectral signatures, (i.e. the information from the multispectral image has priority over the data from the panchromatic one). The performance of the fusion technique is always region-based and highly dependent on the actual scene content. For example, large homogeneous areas such as water reservoirs do not need to be spatially enhanced since the resolution power of the multispectral band is sufficient for these regions. In fact, the information injected from the image with higher spatial resolution disturbs the spectral characteristics of the area since the highly resolved imagery usually has a lower signal-to-noise ratio. On the other hand, there are regions which definitely require spatial enhancements, such as urban zones or boundary regions between two homogeneous areas.

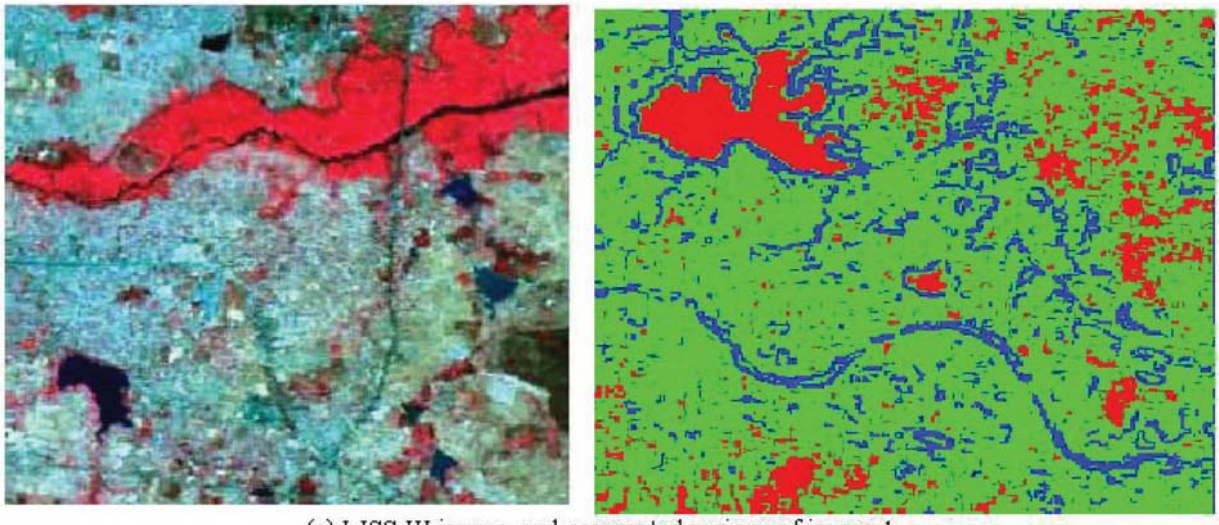


(a) LISS III (b) PAN

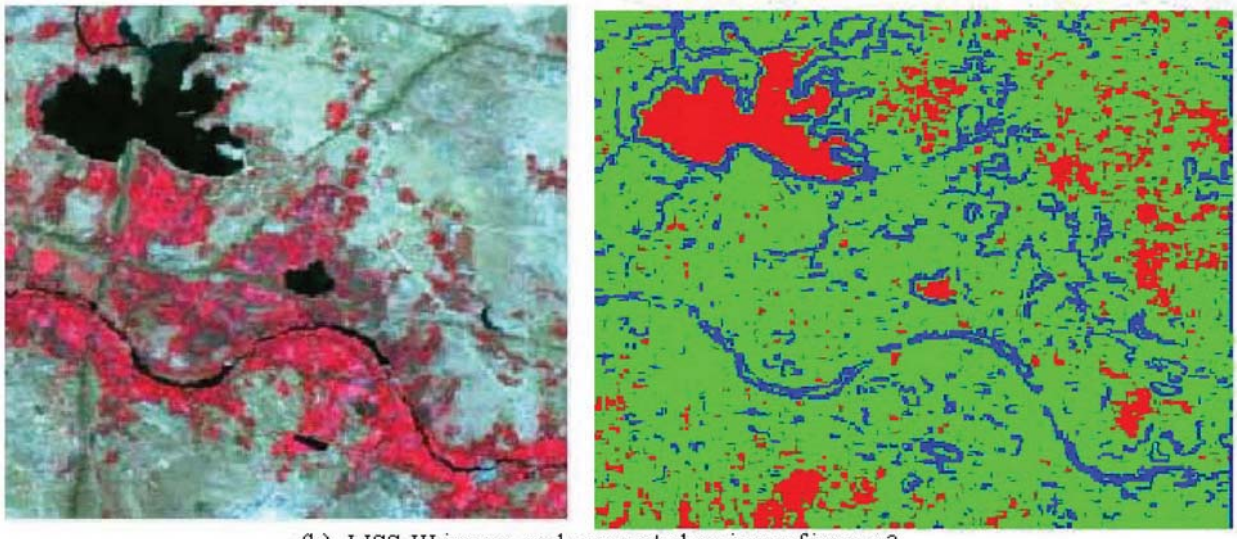
(c) BROVEY (d) MUL

(e) PCA (f) WAVELET

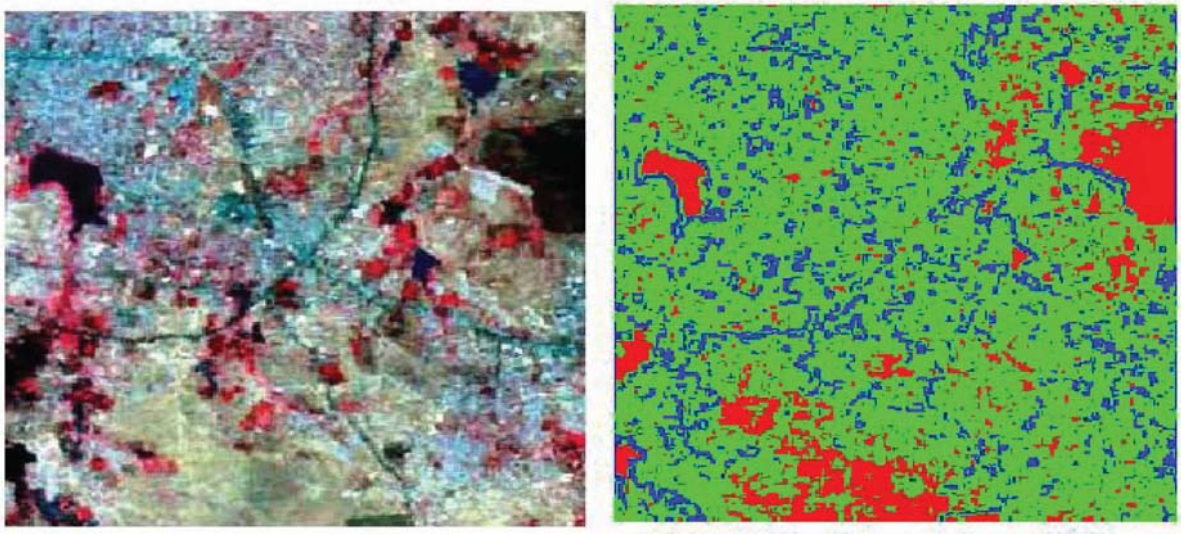
Figure 1: LISS III, PAN and Fused Images of Image 1



(a) LISS III image and segmented regions of image 1



(b) LISS III image and segmented regions of image 2



(c) LISS III image and segmented regions of image 3

Figure 2: LISS III and segmented regions of the three images

The decision was to measure spectral and spatial changes (in terms of enhancement or degradation) between the original multispectral image *m* and the fused product m_f. The content based approach is utilized by splitting the original multispectral image into different regions with various spatial characteristics and performs the fusion evaluation for each particular region independently. Thus, a measure to determine the spatial variability of the scene is needed. The standard deviation of the pixel values inside a square window is chosen for the reason that it represents the scatter of the data. The sliding window with the size of 3×3 pixels is used and the standard deviation value inside the window is assigned to the central pixel as a salience measure of this region. The pixels with high values represent regions with high variability of the spatial data in the original image, whereas low values account for homogeneous areas. The newly created image is denoted as m_σ:

$$m_\sigma(x,y)=\left(\frac{1}{n-1}\sum_{W(x,y)}(m(x,y)-\overline{m}(x,y))^2\right)^{\frac{1}{2}}$$

Equation 1

Where $\overline{m}(x,y)=\frac{1}{n}\sum_{W(x,y)}m(x,y)$ and *n* is the number of pixels inside the window $W(x,y)$ centered at pixel (x,y). The next step is to segment m_σ in order to mark regions with similar spatial characteristics. An example for the histogram of typical m_σ is shown below.

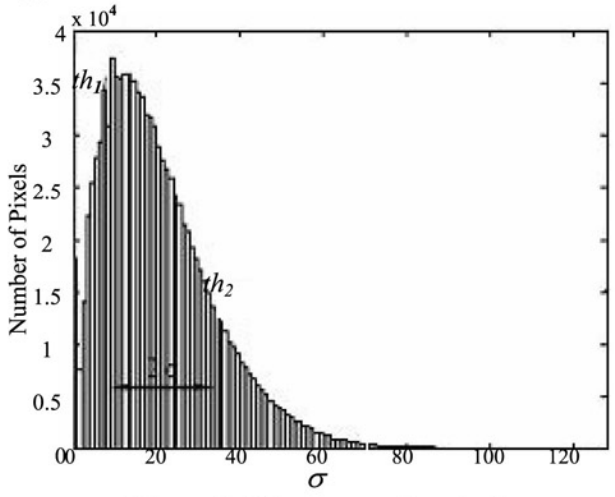


Figure 3: Histogram of typical m_σ

From the histogram shown two thresholds th_1 and th_2 are defined. The pixels with values less than th_1 are considered to represent homogeneous areas; pixels with values larger than th_2 represent highly non-homogeneous regions with the extreme variability of the spatial features.

The pixels with values between th_1 and th_2 indicate areas with moderate salience. Thus, the thresholds are determined in an unsupervised fashion by: $th_1=\mu(m_\sigma)-\sigma(m_\sigma)$, $th_2=\mu(m_\sigma)+\sigma(m_\sigma)$, where μ denotes the mean and σ denotes the variance of m_σ. Subsequent to the process of thresholding, the three individual binary maps with the same size as the original multispectral image are obtained. A pixel value of unity in a map identifies a pixel in the image *m* which belongs to one of the three categories of the regions described above.

3. Performance Evaluation

The performance evaluation is achieved by examining the spectral and spatial changes of *mf (*fused image*)* with respect to *m* (multispectral image*)* within each of the three regions. The signal to noise ratio is also evaluated for multispectral image and various fused images.

3.1 Spectral Evaluation

Let m^i be all the pixels of *m* which constitute region *i* with *i*=1…3, while mf^i are the pixels with the same coordinates as in m^i but from *mf*. The root mean square of the differences, i.e. rms (mf^i-m^i), is used to calculate the spectral changes of three regions (homogeneous, moderate and highly non-homogeneous areas).

3.2 Spatial Evaluation

Spatial quality evaluation of the fused image is a more complex task and generally based on perceptual inspection. Alterations of the image gradients are proposed as a measure of spatial changes. The first order derivative gradients are used in edge detection algorithms since the absolute value of the first derivative tends to be higher in regions with strong presence of edges. Thus, after the fusion, an increase of gradient values inside the regions with edges is expected to be observed. The Roberts cross difference operator is used to calculate the gradient values and to calculate spatial changes, primarily the Sobel's gradient operator is applied to both *m* and *mf*. The filtered images are denoted as *R*(*m*) and *R*(*mf*), respectively. Subsequently, sums of the gradients inside the three regions are calculated individually for both *R*(*m*) and *R*(*mf*).

The normalized difference of the sums is a measure of spatial enhancement (or degradation), whereby the normalization is performed with respect to the number of pixels belonging to the individual region. The final formula for spatial changes using the Roberts gradient is: $[\sum Ri\ (Mf)-\sum Ri\ (M)]/Ni$.

3.3) Signal to Noise Ratio

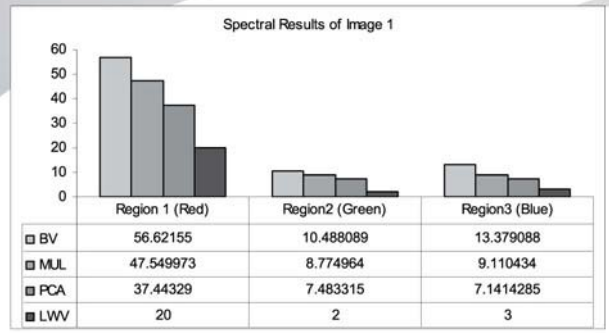
The image variance equals the summation of signal variance and noise variance. The standard deviation of gray value in a homogeneous image area is regarded as the estimation of noise variance. Then, the difference of image variance and noise variance is equal to signal variance. The signal variance divided by noise variance yields the signal to noise ratio (SNR) value.

4. Discussion of Results

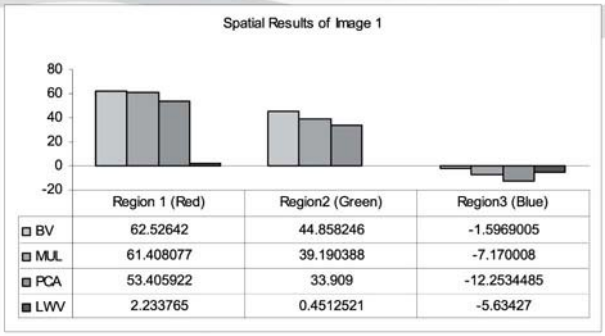
The fusion of low-resolution multispectral data (IRS 1D LISS III; 23.5m resolution) and a high resolution panchromatic data (IRS 1D PAN; 5.8m resolution) was attempted using image fusion techniques such as PCA, Multiplicative merge, Brovey transform (Erdas Imagine software, 8.5) and Lifting Wavelet transform (Valens). This study is carried out using three images (Image 1, Image 2, Image 3) over the Hyderabad city, AP, India and its vicinity with both urban and rural features. The images used are corrected for system errors and processed in order to reduce speckle and atmospheric influences. Consequently, the images were co-registered to make pixels coincide. An improper co-registration of images causes the formation of artifacts in the fused image. Images are not registered properly if the rms error is high. Hence the images considered for image fusion in this study are co-registered to an rms error of 0.2. In this paper the fused images are exposed only for Image1 (Figure 1) due to space availability. Then the three images used in the study (Image 1, Image 2 and Image 3) are partitioned into three regions. The homogeneous regions are denoted "Region 1", moderate salience areas as "Region 2" and highly non-homogeneous areas as "Region 3" respectively (Figure 2). The quality assessment of various fusion techniques is performed using spectral and spatial changes of the fused images (Figure 4a, 4b, 4d, 4e, 4g, 4h) and with the segmented regions of the original multispectral image. The results are given for the three test images. It is ascertained that Multiplicative and Brovey transform methods of image fusion techniques have more spectral changes in all the three regions. As Lifting Wavelet preserves the spectral content of the multispectral image, the spectral changes are less for this method of fusion. The spectral changes are also more in region 1 when compared to region 2 and region 3 in all the three images taken for study. Hence it is shown that Lifting Wavelet technique of image fusion is best in preserving the spectral content when compared to other methods of image fusion. From the results obtained about spatial changes, it is observed that Lifting Wavelet technique has less spatial variations, compared other fusion techniques. Also, in Lifting Wavelet transform, spatial changes are less in regions 2 and 3 than region 1.The results for highly non-homogenous areas have exposed another problem that has to be considered in the development of new fusion algorithms. As these regions have relatively high variability, further spatial enhancement will not improve the interpretability significantly, while spectral distortions become unavoidable. The signal to noise ratio is also evaluated for the various fusion techniques using three test images (Figure 4c, 4f, 4i). It is observed that the Lifting Wavelet transform technique has high signal to noise ratio compared to other techniques which is an indication of information improvement rather than noise. Hence image fusion is always a trade between the spectral information of the multispectral image and spatial information of the panchromatic band. By means of the techniques of fusion used in this study it is easier to evaluate the contributions of these components in the fused image and opt for the appropriate fusion method which satisfies the user needs.

5. Conclusions

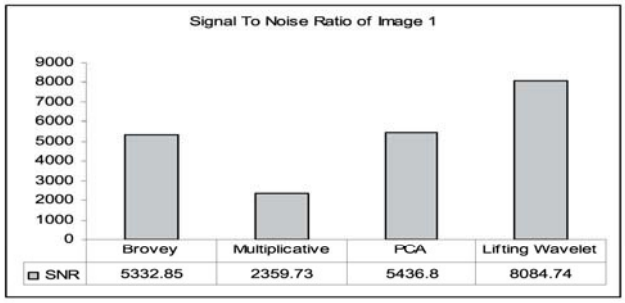
The performance of different fusion techniques are evaluated with objective measures in the field of satellite remote sensing. The spatial and spectral changes facilitate comparative study of various fusion techniques. It has been corroborated that PCA fusion technique preserves more spectral information as compared with Multiplicative and Brovey Image fusion techniques. The Multiplicative fusion technique preserves more spatial information as compared with PCA and Brovey image fusion techniques. In Lifting Wavelet transform, spectral changes are less in regions 2 and 3 in all the three images compared to region 1. It is evident that spatial changes are less in Lifting Wavelet compared to other image fusion techniques. The signal to noise ratio is also high for Lifting Wavelet technique in all the three images. Hence, it is ascertained that Lifting Wavelet transform technique is unsurpassed amongst all the fusion techniques irrespective of the characteristics of the image. There is no requirement for a priori information. The negative values are an indication of the changes in the magnitude resulting in algebraic manipulations. Further analysis to find out the directionality would be appropriate to quantify the significance of negative values. Improving the accuracy of the region classification routines and band-wise quality assessment of fusion techniques is a possible topic for future research.



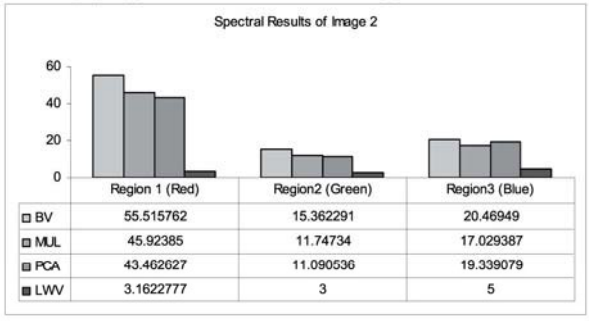
(a) Spectral Results of Image 1



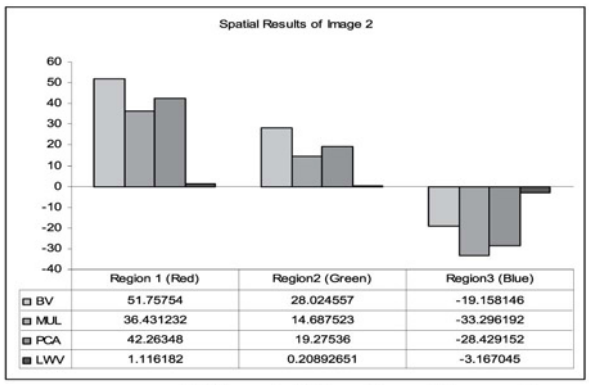
(b) Spatial Results of Image 1



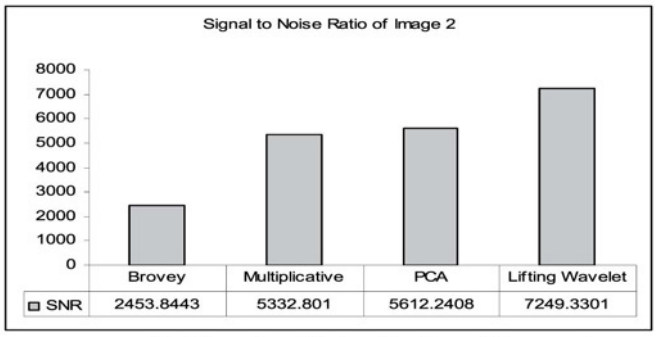
(c) Signal to Noise Ratio of Image 1



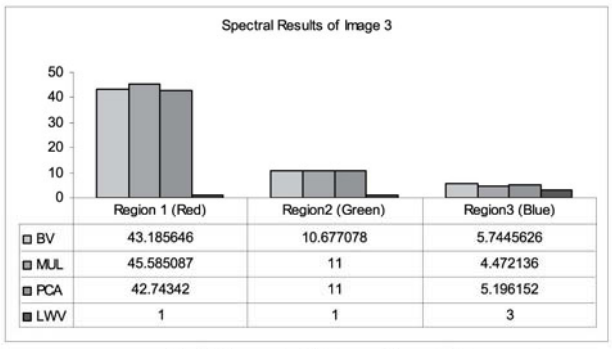
(d) Spectral Results of Image 2



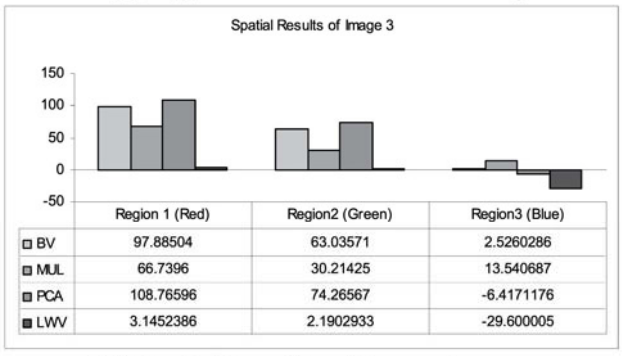
(e) Spatial Results of Image 2



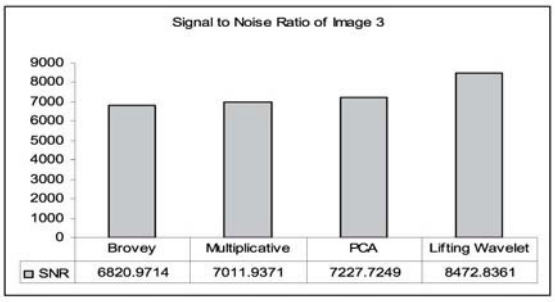
(f) Signal to Noise Ratio of Image 2



(g) Spectral Results of Image 3



(h) Spatial Results of Image 3



(i) Signal to Noise Ratio of Image 3

Figure 4: Quality Assessment of Different Image Fusion Techniques

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