PERFORMANCE ANALYSIS OF IMAGE FUSION TECHNIQUES BY IMAGE SEGMENTATION

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ABSTRACT:

In remote sensing, the satellite images acquired form sensors exhibit either good spectral characteristics (multispectral data) or high spatial characteristics (panchromatic data). Image fusion is required to increase the interpretation quality of images. In this paper an attempt 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 between the original multispectral image and the fused image are used to assess the performance of the fusion technique. A few 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 show that the content based segmentation is objective and do not require any priori information. The performance evaluation proves 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. The fused image should have more complete information than the multispectral image and the panchromatic image. Image fusion is more convenient and economical than designing an advanced sensor with both resolution characteristics. Image fusion can be performed at three different levels according to the stage at which fusion takes place at Pixel, Feature and Decision level (Pohl and Genderen, 1998). Feature level requires algorithms capable of recognizing objects in the various data sources, i.e. based on statistical characteristics of dimension, shape, edges etc. Segmentation procedures can be useful 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

Image segmentation is a critical component of any image analysis and/or pattern recognition system. The desirable characteristics that good image segmentation should exhibit with reference to gray-level images are that the regions of image segmentation should be uniform and homogeneous with respect to some characteristics such as gray tone or texture. The concept of region growing and merging algorithm to color was studied (Tremeau et al ,1997) and some region based algorithms are tested to compare their limits. Efficient graph-Based Image Segmentation technique was reviewed and the problem of segmenting an image into regions is addressed (Pedro Felzenszwalb 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. In new automatic image segmentation method (Jianping Fan 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. There are many methods available for image quality evaluation, which include visual comparison, statistical comparison and least mean square deviation computation and variance tabulation. The assessment of image fusion techniques was based on visual and graphical inspection. The assessment of image fusion is done by measuring the quantity of enhanced information in fused images using entropy and image noise index (Lau Wai Leung et al, 2001). Variance is used as quality parameter suggested measures based on local variance computed over a three-by-three pixel window (M.Beauchemin et al, 2002). A spatial quality assessment approach is also based on the sensor's point spread function estimation (Li, 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. 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. Thus, image segmentation and estimation of the fusion performance is still an open problem, which 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 technique 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 autonomous segmentation is one of the most difficult tasks in digital image processing. In general, the recognition depends on the accuracy of segmentation.

The goal of the fusion is to enhance the spatial resolution of the multispectral imagery while preserving the spectral signatures. 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. However, careful investigations showed that the performance of the fusion technique is always region-based and highly dependent on the actual scene content. 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 was chosen for this purpose since 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:

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

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 $W(x,y)$. 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.
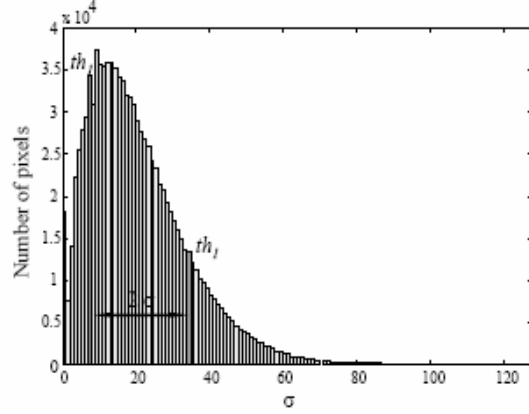
From the histogram shown two thresholds th_1 and th_2 are defined. The pixels with values less than th_1 are considered to represent homogeneous areas; pixels with values larger than th_2 represent highly non-homogeneous regions with the extreme variability of the spatial features. The pixels with values between th_1 and th_2 indicate areas with moderate salience. For the test cases the corresponding histograms of the m_σ resembled Gamma distributions with a confidence interval of 95%. 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. After 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. QUALITY ASSESSMENT

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.

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 usually based on perceptual inspection. The 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. To calculate spatial changes, first the Sobel's gradient operator is applied to both m and mf. The filtered images are denoted as $R(m)$ and $R(mf)$, respectively. Then, the 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: $[\sum Ri(Mf) - \sum Ri(M)]/Ni$.

4. DISCUSSION OF RESULTS

The fusion of low-resolution multispectral data (IRS 1C LISS III; 23.5m resolution) and a high resolution panchromatic data (IRS 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 (C.Valens). This study is carried out using the part of the image of Hyderabad city, AP, India and its vicinity with both urban and rural features. The LISS III image (Figure 1) and panchromatic image (Figure 2) of the part of the Hyderabad image used in this study are corrected for system errors and processed in order to reduce speckle and atmospheric influences. Then the images are co-registered to make pixels coincide. An improper co-registration of images causes the formation of artifacts in the fused image. The 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 only PCA method of fused image is shown (Figure 4) due to space availability. Then the part of the Hyderabad image used in the study is 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 3). The quality assessment of various fusion techniques is performed using spectral and spatial changes of the fused images (Figure 5 and Figure 6) and with the segmented regions of the original multispectral image.
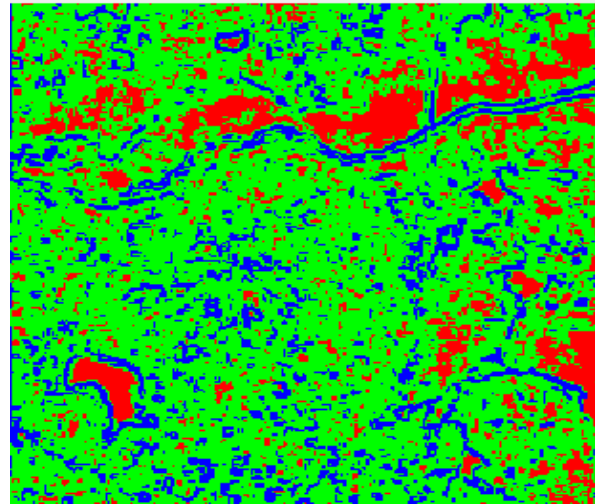

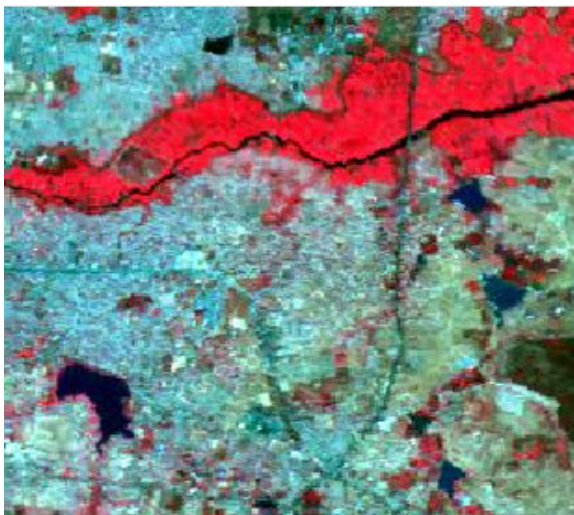Figure 3. Regions of part of Hyderabad image

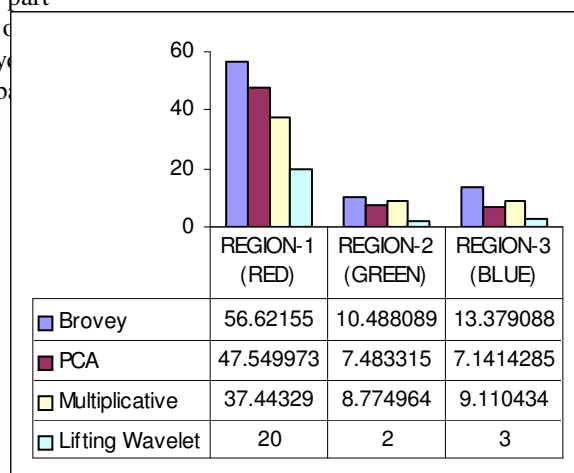Figure 1. LISS III image of part of Hyderabad

Figure 4. PCA fused image

	REGION-1 (RED)	REGION-2 (GREEN)	REGION-3 (BLUE)
■ Brovey	56.62155	10.488089	13.379088
■ PCA	47.549973	7.483315	7.1414285
□ Multiplicative	37.44329	8.774964	9.110434
□ Lifting Wavelet	20	2	3

Figure 5. Spectral results of part of Hyderabad image

Figure 2. PAN image of part of Hyderabad

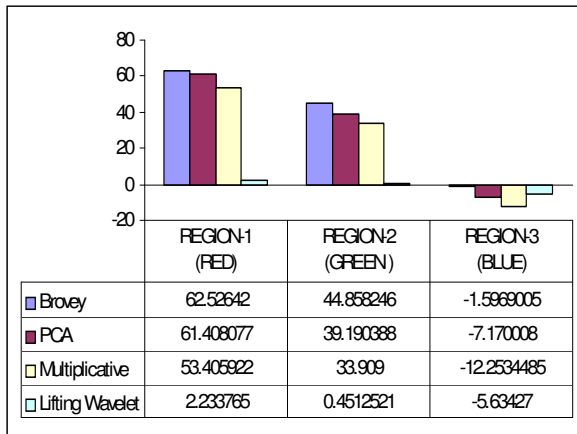|	REGION-1 (RED)	REGION-2 (GREEN)	REGION-3 (BLUE)
Brovey	62.52642	44.858246	-1.5969005
PCA	61.408077	39.190388	-7.170008
Multiplicative	53.405922	33.909	-12.2534485
Lifting Wavelet	2.233765	0.4512521	-5.63427

Figure 6. Spatial results of part of Hyderabad image

From the results it can be clearly seen that the proposed fusion techniques are in the agreement with previous literature. It is shown that Multiplicative and Brovey transform methods of image fusion techniques have more spectral changes in all the three regions. As PCA preserves the spectral content of the multispectral image, the spectral changes are less for this method of fusion. Moreover as the area of Region 2 is having high intermediate variance, the spectral changes are also more when compared to Region 1 and Region 3. Hence it is shown that PCA method of image fusion is best in preserving the spectral content when compared to Brovey and Multiplicative transform methods of image fusion.

From the results obtained for the spatial changes, it is observed that PCA method of fusion has more spatial variations, compared to Brovey and Multiplicative methods. Also, the spatial changes are less for multiplicative method in all the three regions as the gray level value of the multispectral image is modified by the panchromatic image. The test results for highly non-homogenous areas have shown 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. Hence image fusion is always a trade between the spectral information of the multispectral image and spatial information of the panchromatic band. By the methods of fusion used in this study it is easier to evaluate the contributions of these components in the fused image and to choose 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 help in comparative study of various fusion techniques. It has been proved 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. Apart from this, the Lifting Wavelet transform yielded better results when compared with the conventional image fusion techniques. The Lifting Wavelet transform technique is proved to be the best of all the fusion techniques irrespective of the characteristics of the image.

There is no need 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.

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