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Assessment of Different Fusion Methods Applied to Remote Sensing Imagery

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***Abstract*— Image fusion is a formal framework for combining and utilizing data originating from different sources. It aims at producing high resolution multispectral images from a high-resolution panchromatic (PAN) image and low-resolution multispectral (MS) image. This fused image must contain more interpretable information than can be gained by using the original image. Ideally the fused image should not distort the spectral characteristics of multispectral data as well as, it should retain the basic colour content of the original data. There are many data fusion techniques that can be used which include Principal Component Analysis (PCA), Brovey Transform (BT), Multiplicative Transform (MT) and Discrete Wavelet Transform (DWT). One of the major problems associated with a data fusion technique is how to assess the quality of the fused (spatially enhanced) MS image. This paper presents a comprehensive analysis and evaluation of the most commonly used data fusion techniques. The performance of each data fusion technique is analyzed in both qualitatively and quantitatively. Then, the methods are ranked according to the conclusions drawn from visual analysis and the experimental quantitative results. To study this, a Graphical User Interface (GUI) is developed using MATLAB for image fusion to make the research outcomes available to the end user for commercial and economical activities. Due to the demand for higher classification accuracy and the need in enhanced positioning precision, there is always a need to improve the spectral and spatial resolution of remotely sensed imagery. These requirements can be fulfilled by the utilization of image data fusion techniques in classification problems at a significantly lower expense.**

***Keywords*— Image Fusion, Principal Component Analysis, Brovey Transform, Multiplicative Transform and Discrete Wavelet Transform.**

I. INTRODUCTION

Image fusion is a process of combining two or more images, to obtain a new and composite Image using a certain algorithm. Image fusion is to integrate different data in order to obtain more information than that can be derived from each of the single sensor data alone. Image fusion has been applied to achieve a number of objectives like image sharpening, improving geometric correction, complete data set for improved classification, change detection, substitute missing information, replace defective data etc., [1], [2], [12], [14].

Data fusion is a formal framework, expressed as means and tools for the alliance of data originating from different source gives "different quality" means that will depend [2] upon the application. Image fusion is mainly used to enhance the visual interpretation, and improving the image classification because of the following reasons:

- Image fusion is based on the fusion of data from different satellite sensors. Because of the difference of the various parameters and phase between different sensors, as well as the inevitable registration error, lead to the fusion classification results unsatisfactory.
- Although the same sensor system provided different spatial resolution images, resulting in poor classification effect, because of its low spatial resolution.
- Because of the unreasonable fusion or classification method make the failure in classification.

A. *Image Fusion Principle*

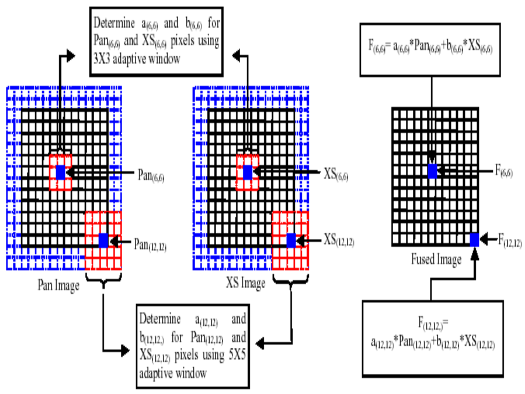

Fig. 1 Construction of fused pixels using a PAN and XS images

The fused image is seen as a linear combination of the PAN and XS images. To create a new fused pixel, corresponding pixels in the PAN and XS images are multiplied by the weighting factors "a" and "b" respectively. The sum of the new weighted pixels from the PAN and XS images will form the new fused pixel. This can be expressed by the following expression

$$F_{k(m,\,n)} = n_{(m,\,n)} * I_{0(m,\,n)} + b_{(m,\,n)}\ I_{k(m,\,n)} \qquad (1)$$

Where, m and n are the row and column numbers, k = 1, 2, 3, …., N (N = number of XS bands); F_k is the fused image, I_o is PAN image and I_k is the XS band. The above relationship is only valid for a certain window, i.e., the 'a' and 'b' coefficients must be determined by window.

For the simplicity of notations, the derivation uses 1-D subscript 'i' for window locations and the band number 'k' is ignored. For simplicity, 3x3 and 5x5 windows are used in the Fig. 1. To calculate a $_{(6,\,6)}$ and b $_{(6,\,6)}$, 3x3 window is selected such that PAN (6, 6) and XS (6, 6) pixels are the centre pixels of the 3x3 window. Once a (6, 6) and b (6, 6) coefficients are determined using the two criteria introduced above and the fused pixel F (6, 6) is calculated via equation (1). If user wants the fused image with the same size of the input images, then padding process will be needed for the border regions of the input images. The blue pixels surrounding the input images represent the padding area. To calculate F (12, 12) with a 5x5 window, PAN and XS images are enlarged such that all the pixels within the window have a pixel value. There are various padding approaches in the literature (e.g., zero padding approach which extends the images with zeros). In this study no padding was used. Therefore, the fused images are smaller in size depending on the window sizes used [5], [12], [14], [20].

B. *Levels of Image Fusion*

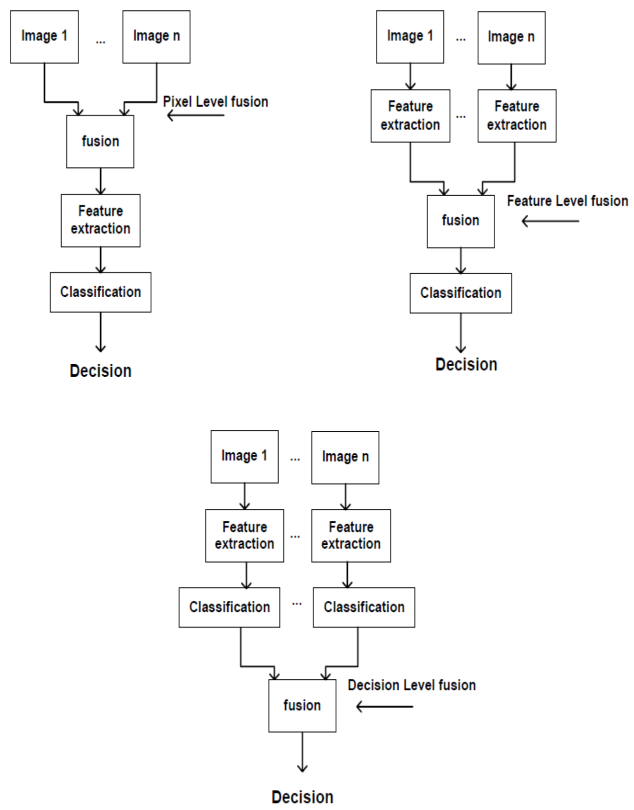

Fig. 2 Different levels of image fusion

Image fusion takes place at three different levels: pixel, feature, and decision [1]. In pixel-level fusion, a new image is formed whose pixel values are obtained by combining the pixel values of different images through some algorithms. The new image is then used for further processing like feature extraction and classification. In feature-level fusion, the features are extracted from different types of images of the same geographic area. The extracted features are then classified using statistical or other types of classifiers. In decision-level fusion, the images are processed separately. The processed information is then refined by combining the information obtained from different sources and the differences in information are resolved based on certain decision rules. The Fig. 2 provides a visual interpretation of the different levels of fusion.

II. BACKGROUND FOR DATA SOURCE

A. *Study Area*

The study area considered for the research work is a semi-urban area of Arsikere situated in Hassan District, Karnataka State, India and its geographical coordinates are 13° 18' 50" North, 76° 15' 22" East and its original name (with diacritics) is Arsikere. It has an average elevation of 807 meters (2647 feet). The image dimension of the study area is 607×645 pixels in MS data and a visual band aerial photograph of the study area is 726x607 pixels of PAN data.

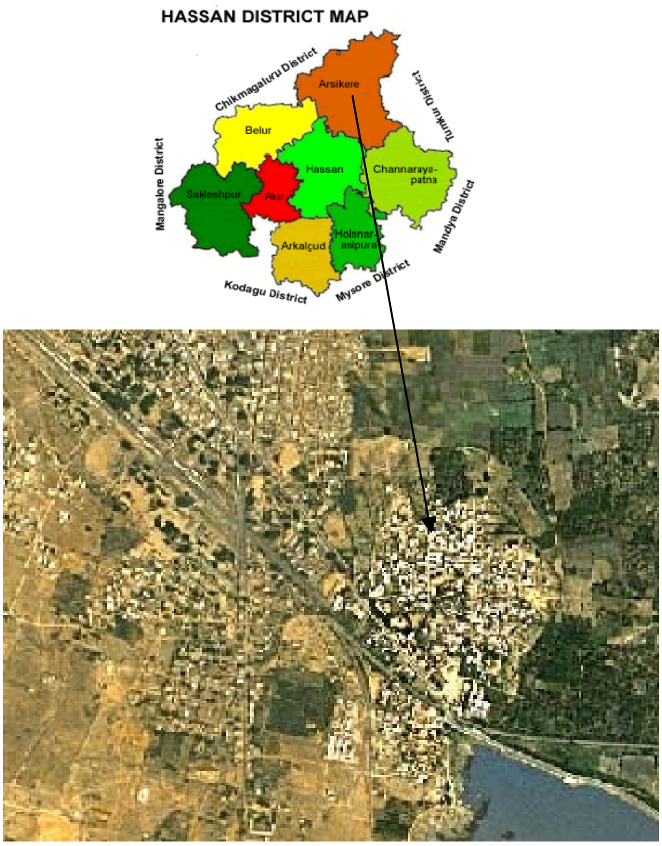

Fig. 3 Visual Band Aerial Photograph of Study Area, Arsikere, Karnataka

B. *Data Products*

Table 1 gives the specifications of image data products used in this work. The data are of LISS-IV (Linear Imaging and Self Scanning) sensor of IRS P-6 satellite (Indian Remote Sensing Satellite). Another data used is Panchromatic obtained from the Visual band multi spectral data downloaded from www.wikimapia.com.

TABLE I
DETAILS OF THE DATA PRODUCTS USED

Sl. No	Satellite and Data type	Date of Acquisition	Spectral Resolution	Spatial Resolution
1.	IRS P-6 (Resourcesat1) Multi-spectral	July 2002	Green(0.52-0.59μm); Red (0.62-0.68 μm); Infrared(0.77-0.86 μm);	5.8m
2.	Wikimapia.com Panchromatic	March 2010	-----	2.5m

C. Spatial Resolution

Spatial resolution of an imaging system is expressed as the area of the ground represented by one pixel. The instantaneous field of view (IFOV) is the ground area sensed by the sensor at a given instant in time. The spatial resolution is dependent on the IFOV. The finer the IFOV is, the higher the spatial resolution. Spatial resolution is also viewed as the clarity of the high frequency detail information available in an image. As the spatial resolution increases the details in an image are clearer.

As one can see from the images, the detail information in the images becomes clearer as the spatial resolution increases from low to high. Spatial resolution is usually expressed in meters or feet in remote sensing. In medical imaging, it is expressed in millimetres [1], [2], [13].

D. Spectral Resolutions

TABLE II
THE DIFFERENT RANGES OF WAVELENGTHS IN THE EMR

Spectrum	**Wavelength**
Gamma rays	< 0.03 μm
X rays	0.03 - 0.3 μm
Ultraviolet rays	0.3 - 0.4 μm
Visible region	0.4 - 0.7 μm
Infrared region	0.7 - 1.0 μm
Reflected infrared band	0.7 - 3.0 μm
Thermal infrared band	3.0 - 5.0 μm
Radar	0.1 - 30 cm
Radio waves	> 30 cm

Table 2 shows the spectral responses measured by remote sensors over various features often permits an assessment of the type and condition of the features. These responses have often been referred to as "spectral signature".

Spectral resolution is the width within the electromagnetic spectrum that can be sensed by a band in a sensor. The narrower the spectral bandwidth is, the higher the spectral resolution. If the platform has a few spectral bands, typically 4 to 7, they are called multispectral data and if the number of spectral bands in hundreds, they are called hyper spectral data [1], [2], [13].

III. IMAGE FUSION TECHNIQUES

Generally, image fusion methods are based on pixel-level fusion techniques. This type of fusion method losses only the least information, so the accuracy of the pixel level fusion is the highest, but the data transmission and processing is the largest [4], [17].

A. Transformation Based Fusion

1) Principal Component Analysis Method:

The principal component analysis (PCA) is widely used in signal processing, statistics, and many other applications [11]. The PCA involves a mathematical procedure that transforms a number of correlated variables into a set of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. There can be as many possible principal components as there are variables. It can be viewed as a rotation of the existing axes to new positions in the space defined by the original variables. In this new rotation, there will be no correlation between the new variables defined by the rotation. The PCA is widely used for dimensionality reduction and data analysis. The PCA is computed using the Eigen values and eigenvectors of the covariance matrix of the multi-spectral image bands. The Eigen values indicate the variance along the principal components and the eigenvectors denote the direction of the principal components. The Eigen values are arranged in decreasing order of magnitude. The transformation matrix for computing principal components is obtained by arranging the eigenvectors in the order corresponding to that of the Eigen values. Thus the first principal component corresponds to the direction of the highest Eigen values or maximum variance. The second principal component corresponds to the second maximum variance and so on.

2) Intensity-Hue-Saturation Method:

The Intensity-Hue-Saturation (IHS) transformation decouples the intensity information from the color carrying information [15]. The hue attribute describes a pure color and saturation gives the degree to which pure color is diluted by white light. This transformation permits the separation of spatial information into one single intensity band. There are different models of IHS transformation. The models differ in the method used to compute the intensity value. Hexacone and triangular models are two of the more widely used models [3], [15]. The hue and saturation values are computed based on a set of complex equations. The intensity value for the hexacone model and triangular model is computed as shown in equations;

$$I = \max(r, g, b) \qquad \ldots\ldots (2)$$

$$I = \frac{R + G + B}{3} \qquad \ldots\ldots (3)$$

$$I = \frac{\max(R,G,B) + \min(R,G,B)}{2} \qquad (4)$$

This model ignores one of the three components to compute the intensity. The changes in the intensity values are not distributed evenly in all the three R, G, and B components when the inverse transform is performed. All the three models have different set of equations to compute the hue and saturation values.

3) Standardized Principal Component (SPC) Transformation:

This method uses the correlation matrix to determine the transformation matrix instead of the covariance matrix. The main advantage in comparison to the principal component transformation is that all bands are considered equally important [2]. This is of particular interest for the imagery under investigation as the near infrared band exhibits a superior variance and thus would dominate the fusion process.

B. Additive and Multiplicative Technique

1) Brovey Transform:

The Brovey transform, named after the it's author. Ratio images are very useful in change detection. The Brovey transform is a formula based process that is based on the band to display in a given colour, the sum of all the colour layers, and the intensity layer. The Brovey transform uses a formula that normalizes multispectral bands used for an RGB display, and multiplies the result by any other higher resolution image to add the intensity or brightness component to the image. The formula is as follows:

$$\begin{aligned} R &= (R / (R + G + B)) * I \\ G &= (G / (R + G + B)) * I \\ B &= (B / (R + G + B)) * I \end{aligned} \qquad (5)$$

Where, R = Red, G = Green, B = Blue, I = Intensity
The Brovey transform can also be expressed as,

$$DN_{\text{fussed MSI}} = \frac{DN_b}{DNb_1 + DNb_2 + \ldots\ldots\ldots + DNb_n} DNpan \quad \ldots. (6)$$

The Brovey transform provides excellent contrast in the image domain but affects the spectral characteristics a great deal [4], [17].

2) Multiplicative Technique (MT):

The multiplicative technique (MT) is grouped under the arithmetic method which uses the four possible arithmetic methods (addition, subtraction, division and multiplication) to incorporate an intensity image into an achromatic image. The MT algorithm is based on the following relation,

$$\begin{aligned} &DN\,R\,(\text{new}) = DNR * DN\ PAN \\ &DN\,g\,(\text{new}) = DN\,g * DN\ PAN \\ &DN\,B\,(\text{new}) = DN\,B * DN\ PAN \end{aligned} \qquad (7)$$

Where, DN*R*, DN*G* and DN*B* = Digital number of the corresponding pixel belonging to the R, G and B bands

DN PAN = Digital number of the corresponding pixel belonging to the panchromatic band

DN new = New digital number of the corresponding pixel of the respective band

3) Colour normalised (CN) transformation:

The colour normalised transformation [6] fuses the two spectral and spatial data sets assuming there is a certain spectral overlap between the multispectral bands and the more highly resolved panchromatic band. This constraint is violated for the near infrared band XS3 and results in poor fusion results. Equation (5) shows the merging process whereby the additive constants avoid division by zero.

$$XS_i^R = \frac{3(XS_i^R + 1)(P_N + 1)}{\sum_I XS_i^R + 3} - 1 \qquad (8)$$

C. Wavelet Method

The wavelet transform [6], [7], [8], [10], [16] is a mathematical tool extensively used in image analysis and image fusion. Using multi-resolution analysis, the multispectral and the panchromatic images were decomposed into an orthogonal wavelet representation at a coarser resolution, which consisted of low frequency approximation image and a set of high frequency detail images. The detail images from the high resolution panchromatic image are incorporated into the decomposed multispectral images at a level the resolution of the ground cover matches and the inverse transform is taken.

The various steps involved in merging images using wavelet method are as follows;

- Resample the multispectral image to make its pixels size equal to that of the panchromatic images. The multispectral and panchromatic images are geometrically corrected using ground control points, so that they can be merged.
- Apply the discrete Wavelet transform to the "histogram-matched" panchromatic image and to the "resampled" multispectral image, using the Daubechies four coefficient wavelet basis. Four half-resolution images (C_a, C_h, C_v and C_d) are obtained from each multispectral and panchromatic full resolution image.
- Repeat step 2 to generate wavelets for each level till the resolution of the image matches by using the approximation image as input for each level.
- Using the detail images (C_h , C_v and C_d) from each decomposition, generate the detail images that are going to be replaced in the multispectral decomposition.

The detail images can be generated using the following formula;

$$\begin{aligned} C_h^* &= (C_h^p + C_h^m)/2 \\ C_V^* &= (C_v^p + C_v^m)/2 \\ C_d^* &= (C_d^p + C_d^m)/2 \end{aligned} \qquad \ldots\ldots \qquad (9)$$

Where, C_h^*, C_v^*, C_d^* are the detail images generated that are going to be replaced in the multi-spectral decomposition.

C_h^p, C_v^p, C_d^p are the detail images generated from the panchromatic data.

C_h^m, C_v^m, C_d^m are the detail images generated from the multi-spectral data

D. Filter Fusion Method:

1) High-pass Filter Fusion Method (HPF)

High-pass filter fusion method a method that make the high frequency components of high-resolution panchromatic image superimposed on low resolution multispectral image, to obtain the enhanced spatial resolution multispectral image. The formula is as follows**:**

$$F_k(i,j) = M_k(i,j) + HPH(i,j) \qquad (10)$$

In the formula, $F_k(i,j)$ is the fusion value of the band K pixel (i,j), $M_k(i,j)$ the value of multi-special of band k pixel (i,j), HPH(i.j) show the high frequency information of the high resolution image.

2) Smoothing Filter-based Intensity Modulation:

Smoothing Filter-based Intensity Modulation, which a brightness transformation is based on the smoothing filter. The formula of this arithmetic is as follows:

$$B_{SFIM_I} = \sum_J \sum_K \frac{B_{LOWr,k} \times B_{HIGHf,k}}{B_{MEANf,k}} \qquad (11)$$

In the formula B_{sfim} is the fusion image generated by this arithmetic, I is the value of the band, J and K is the value of row and line; B_{LOW} is the Low-resolution images, B_{MEAN} is simulate low-resolution images, which can be obtained by low-pass filter.

E. Fusion Based on Interband Relation

1) Regression fusion (RF):

Due to the high correlation between the visible bands, the relation between one of the fused visible wavelength range images and the high resolution band can be expressed by the simple regression shown in Equation (12). The bias parameter a_i and the scaling parameter b_i can be calculated by a least squares approach between the resampled band XS^R i and P_N.

$$XS_i^H = a + b * p_{1\ldots n} \quad \ldots\ldots (12)$$

The regression technique is not suitable for the near infrared band since the global correlation is weak. However, significant improvements can be obtained using a local approach. Instead of computing the global regression parameters, the a_i and b_i parameters are determined in a sliding window.

2) Look-up-table (LUT) Fusion:

The regression method suffers even for local processing of the near infrared band from the use of the least squares approach. A non-linear approach like the use of lookup-tables helps to overcome this deficit. The up-sampled versions of the multispectral bands are compared with the corresponding high-resolution pixels using a local pixel neighbourhood. Finally the radiance values of the bands XSRi are manipulated with respect to the generated tables. Care must be exercised in choosing the size of the neighbourhood and in preventing artifacts.

IV. Evaluation of Fusion Techniques

A. Qualitative Evaluation (Visual Analysis)

The resulting images obtained from different conventional techniques had erosion scars and some of the deposition areas enhanced related to the other targets in the images. PCA looks much closer to Multi-spectral band in colour hence look more vivid in PCA than BT. Further, PCA is brighter than BT and MT; MT looks dull and smoky. Next to PCA it is the BT which is closer to Multi-spectral data. In brightness retaining quality too the fusion technique is found to be bright and better preserving the original Multi-spectral details. When all the visual evaluation are put together, the PCA is found to be bright and better in preserving the original Multi-spectral details; the BT ranked the second and MT stand in the last in retaining spectral quality. However for these approaches one can verify that it was not possible to obtain a good detail. For example, grass, natural fields and vegetation cover in the early growing stage were not well discriminated. It was also possible to notice a defocusing in the images, which made the erosion scars look like stains instead of linear feature [3], [19].

Among the conventional techniques, it was observed that PCA seems to give the best result of image fusion. Discrete Wavelet fused image has a "better look" evident the erosion scars, showing them with clear and pale tones. Due to preservation of spectral characteristics, it was possible to discriminate more precisely other targets existing in the image. After the spatial resolution enhancement, it was also possible to identify several small features of landslides and the colour scheme is also as good as the original image that were not identified using other fusion approach [3], [19].

TABLE III
VISUAL ANALYSIS OF FUSION METHODS

Methods	Color Recovery	Sharpness
PCA	Good	Good
BT	Good	Not Acceptable
MT	Not Acceptable	Not Acceptable
DWT	Very Good	Very good

As already mentioned, due to limitation of human vision in terms of distinguishing the number of grey levels, comparison and appreciation by visual method doesn't reveal the exact potentials of the fusion methods. Hence comparison of image statistics was attempted to evaluate the results of fusion using PCA, BT, MT, and discrete wavelet transform methods. It is believed that such a comparison would accurately quantify the loss of information after fusion.

B. Quantitative Evaluation (Spatial and Spectral)

Spatial quality evaluation of the fused image is a more complex task and usually based on perceptual inspection. It can be clearly observed from the fused images that all the image fusion methods sharpen the respective multi-spectral bands. Regarding the preservation of spatial resolution, all discussed image fusion methods behave very similarly. However, a greater resemblance between the panchromatic and the intensity image doesn't mean better preservation of spatial resolution [5], [20].

TABLE IV
VISUAL ANALYSIS OF FUSION METHODS

Fusion Methods	RMSE
BT	62.6215
PCA	56.5499
MT	48.6398
DWT	41.0478

From the result, it can be clearly seen that proposed fusion technique is in agreement with previous literature. For the spatial changes, PCA method of fusion has more spatial variation compared to other technique. Hence image fusion is always a trade off between the spectral information of the multi-spectral image and spatial information of the panchromatic band. It is shown that Multiplicative and Brovey transform has more spectral changes. As PCA preserves the spectral changes as in the multi-spectral images, the multi-pectral changes are less in the DWT fusion method. Hence it is shown that DWT method of image fusion is best in preserving the spectral content when compared to PCA, BT, MT methods of image fusion. Image fusion methods used in this work is easier to evaluate the contribution of these components in the fused image and to choose the appropriate fusion method which satisfies the user need.

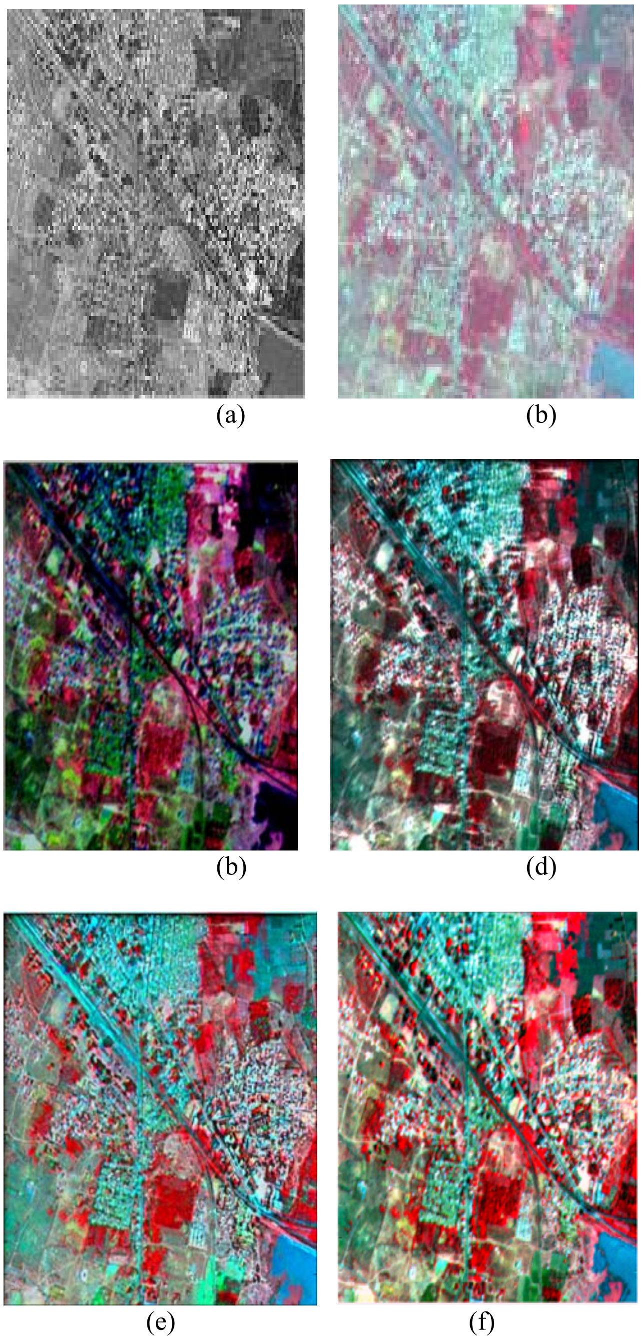

Fig. 4 Snapshot of (a) Panchromatic Image (b) Multispectral Image (c) Principal Component Analysis (d) Multiplicative Technique (e) Brovey Transform (f) Discrete Wavelet Transform Fused Images.

V. CONCLUSIONS

The image fusion methods are used to generate high resolution image that attempts to preserve the spectral characteristics of the original data. There are no generalized criteria for the selection of a particular fusion technique. The selection of the fusion method for an application depends largely on the dataset. For image fusion methods, spatial enhancement and spectral preservation are all critical issues.

In this paper, a new image fusion method is introduced. The fusion outcome is regarded as a linear combination of the input panchromatic and multispectral images. Experimentation with images collected by different sensors reveals that the proposed method is satisfactory. The DWT fusion method presents the best result for both visual and quantitative evaluations. This can be explained by the improvement of the spatial resolution and preservation of the spectral information. Moreover, the DWT method maintains the high spectral content with respect to the original multispectral images. Besides it shows the good spatial content to give an output which is “better looking”.

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 Discrete Wavelet transform yielded better results when compared with the PCA, BT and MT image fusion image. The proposed method has a very smooth transition among different geographic features; however, other fusion methods produce blocking artifacts in the fused images.

The comparative analysis was carried out between the PCA, BT, MT and DWT. The DWT image showed significant improvement for the erosion scars and debris deposition areas identification. Although this approach did show good results for the identification of erosion scars, it is still necessary to evaluate its potential in other areas where such phenomena occurs, and to test the images obtained from other sensors.

techniques. The Discrete Wavelet transform technique is proved to be the best of all the fusion techniques irrespective of the characteristics of the

REFERENCES

[1] B. C. Panda, "Remote sensing: Principles and applications in remote sensing", Pearson Education, pp. 234-567, 1995.

[2] Bethune S., F. Muller, and J. P. Donnay, "Fusion of multi-spectral and panchromatic images by local mean and variance matching filtering techniques", Fusion of Earth Data, 1998.

[3] Bruzzone L., L. Carlin, L. Alparone, S. Baronti, A. Garzelli, and F. Nencini, "Can Multi-resolution Fusion Techniques Improve Classification Accuracy", Proc. SPIE, Vol. 6365, ID No. 636509, 2006.

[4] Chavez P.S., Sides JR S.C. and Anderson J.A., "Comparison of three different methods to merge multiresolution and multispectral data: Landsat TM and SPOT Panchromatic", Photogrammetric Engineering & Remote Sensing 57(3), 295-303, 1991.

[5] C. Pohl, J. L. Van Genderen, "Multi-sensor Image Fusion in Remote Sensing: Concepts, Methods and Application", International Journal of Remote Sensing, 1998. Vol. 99, No. 5, pp. 823-854.

[6] D. A. Yocky, "Image merging and data fusion by means of the discrete two-dimensional wavelet transform", J. Opt. Soc. Amer. A, Vol. 12, No. 9, pp. 1834–1841, 1995.

[7] J. Nunez, X. Otazu, O. Fors, A. Prades, "Simultaneous Image Fusion and Reconstruction using Wavelets Applications to SPOT + LANDSAT images", Vistas Astron. 41 351–357,1997.

[8] L. Chipman, T. Orr and L. Graham, "Wavelets and Image Fusion", Proceedings of the International Conference on Image Processing, Vol.3, pp 23-26, 1995.

[9] L. Wald, T. Ranchin, M. Mangolini, "Fusion of Satellite Images of Different Spatial Resolutions: Accessing the Quality of Resulting Images", Photogrammetric Engineering and Remote Sensing, Vol. 63, No. 6, pp. 691-699, June 1997.

[10] N. Ouarab, M. Achir, N. Khettal and Y. Smara, "Spatial Enhancement of Satellite Images using Data Fusion Algorithms in the Wavelet Domain", Proceedings of the IEEE/ISPRS joint workshop on Remote Sensing and Data Fusion over Urban Areas, pp.293 – 298, 2001.

[11] P. S. Chavez and A. V. Kwarteng, "Extracting Spectral Contrast in Landsat Themantic Mapper Image Data using Selective Principal Component Analysis", Photogrammetric Engineering and Remote Sensing, Vol.55, pp.339-348, Mar 1989.

[12] R. Gonzalez, R. Woods, "Digital Image Processing", 2nd edition, Prentice Hall, Upper Saddle River, New Jersey, 2002.

[13] Ranchin T. and Wald L., "Fusion of High Spatial and Spectral Resolution Images: the ARSIS Concept and its Implementation", Photogrammetric Engineering and Remote Sensing, Vol. 66, No.1, pp. 49-61, 2000.

[14] Schowengerdt R. A., "Remote Sensing: Models and Methods for Image Processing", 2nd edition, Orlando, FL: Academic, 1997.

[15] Siddiqui Y, "The Modified IHS Method for Fusing Satellite Imagery", In ASPRS Annual Conference Proceedings, 2003.

[16] S. G. Mallat, "A theory for Multi-resolution Signal Decomposition: The Wavelet Representation", IEEE Trans. Pattern Anal. Mach. Intell, 674–693, 11, 1989.

[17] Wang Z., D. Ziou and C. Armenakis, "A Comparative Analysis of Image Fusion Methods", IEEE Trans. Geoscience Remote Sensing, Vol. 43, No. 6, pp. 1391–1402, 2005.

[18] Y. Kiran Kumar, "Comparison of Fusion Technique applied to Preclinical Images: Fast Discrete Curvlet Transform using wrapping technique & Wavelet Transform", Journal of Theoretical and Applied Information Technology, 25(1): 668-674, 2005.

[19] Y. Zhang, "A New Merging Method and its Spectral and Spatial Effects", International Journal of Remote Sensing, Vol. 20, No. 10, pp. 2003-2004.

[20] Zhao Zong-gui, "An Introduction to Data Fusion Method", First Press, 28th Institute of Electricity Ministry, 1998.