COMPARISION OF PIXEL - LEVEL BASED IMAGE FUSION TECHNIQUES AND ITS APPLICATION IN IMAGE CLASSIFICATION

[1]Dammavalam Srinivasa Rao

[1]Associate Professor, Dept. IT, VNRVJIET, Hyderabad, Andhra Pradesh, India.

ABSTRACT: Image fusion has become essential to which more and more general formal solutions to a number of applications are demanded. Several situations in image processing simultaneously require high spatial and high spectral information in a single image. Image fusion is the process of combining information from two or more images of a scene into a single composite image that is more informative and is more suitable for visual perception or computer processing. The image fusion approach has already been implemented in various image processing applications medical imaging, automatic target guidance system, remote sensing, machine vision, automatic change detection, biometrics where exactness in the information content is very important. This paper emphasizes on the comparison of image fusion techniques of Principle Component Analysis (PCA), Intensity-Hue-Saturation (IHS), Bravery Transform (BT), Smoothing Filter-based Intensity Modulation (SFIM), High Pass Filter (HPF) and Multiplication (ML). The image fusion techniques are described and compared along with parameters and utilities. It was shown that SFIM image fusion method has better performance than other methods.

Index Terms: Spatial information, image fusion, remote sensing, change detection, image classification.

1.INTRODUCTION

The objective of image fusion is to integrate complementary information from multiple sources of the same scene so that the composite image is more suitable for human visual and machine perception or further image-processing tasks. Grouping images into meaningful categories using low-level visual features is a challenging and important problem in content-based image retrieval. Using binary Bayesian classifiers, attempt to capture high-level concepts from low-level image features under the constraint that the test image does belong to one of the classes[1].

In image classification, merging the opinion of several human experts is very important for different tasks such as the evaluation or the training. Indeed, the ground truth is rarely known before the scene imaging[2]. While many studies in the field of image fusion of remotely sensed data aim towards deriving new algorithms for visual enhancement, there is little research on the influence of image fusion on other applications. One major application in earth science is land cover mapping. The concept of sensors with multiple spatial information provides a potential for image fusion. It minimises errors of geometric alignment and atmospheric or temporal changes. Image classification can be performed with supervised methods, e.g. maximum likelihood classifier, pixel-based classification, object-based classification, and support vector machines[3].

Landsat ETM+ (Enhanced Thematic Mapper) images multi-spectral bands and panchromatic bands can be used to fuse, to research the image fusion method of different spatial resolution based on the same sensor system and the image classification methodology, evaluate the transmission of each fusion method with the land use classification. Image fusion is mainly used to improving accurate visual interpretation and image classification[4]. The image data of Landsat 7 ETM + panchromatic and multispectral images can be used for fusion. There are many types of feature in this area,the main features include rice, dry land, forest, water bodies, residents of villages and towns and so on.

2. Data Source & Preprocessing Steps:

In this context data sets were collected via IRS 1D satellites using LISS III sensors in both the panchromatic (PAN) mode and multi-spectral (MS) mode by NRSA, Hyderabad, Andhra Pradesh (AP), INDIA. There are many types of feature in this area ,the main features include water, agricultural field, greenery field, open area, residents of urban and so on. Image fusion requires preprocessing steps like 1. Image bands selection and
2.Image registration to prepare the images for usage.

It is important to select the best possible three-band combination that can provide useful information on natural resources for display and visual interpretation. Optimum Band Selection for Image Visualization of Multispectral Data in Relation to Natural Resources Management proposed an algorithm of the best three-band selection for Landsat TM and MASTER image visualization[5].In this study correlation coefficient matrix and OIF index are calculated and selected the bands combinations connected(Table1 and Table 2).

Image registration is a key stage in image fusion, change detection, imaging, and in building image information systems, among others[6]. For efficient use of multisource data in regular remote sensing applications, the problem of automatic image registration must be solved[7]. Image registration include relative and absolute registration, the general requirements of registration is call for the error control within a pixel in the high-resolution images.

Using relative registration method, take the panchromatic band of ETM + images for the reference image, select control points to make geometric correction absolute registration [8],the general requirements of image registration with the multispectral images, in order to reduce loss of spectrum by resample, use the nearest neighbour method to resample, the accuracy of registration is controlled with in pixel, which can meet the need of registrations accuracy.

Table 1 Correlation Coefficient Matrix table

	ETM+1	ETM+2	ETM+3	ETM+4	ETM+5	ETM+7
ETM+1	1					
ETM+2	0.944	1				
ETM+3	0.837	0.919	1			
ETM+4	0.619	0.613	0.438	1		
ETM+5	0.642	0.717	0.711	0.688	1	
ETM+7	0.669	0.786	0.858	0.467	0.889	1

Table 2. The OIF index values of different bands combination(ascending order)

Bands combination	OIF index	Range order	Bands combination	OIF index	Range Order
123	12.784	1	134	22.062	11
124	16.677	2	157	22.721	12
127	17.186	3	357	22.838	13
237	18.048	4	245	23.915	14
125	18.346	5	145	24.313	15
137	19.162	6	247	24.854	16
135	19.687	7	147	25.715	17
235	20.598	8	457	27.439	18
257	21.316	9	347	29.202	19
234	22.162	10	345	29.210	20

3. Common Image Fusion Methods

In this paper, the fusion methods are all based on pixel-level fusion method, pixel-level image fusion method in which the lower resolution multispectral image's structural and textural details are enhanced by adopting the higher resolution panchromatic image corresponding to the multispectral image[9].

3.1 Fused methods

3.1. 1 Principal Component Analysis based Fusion Method

Principal component analysis aims at reducing a large set of variables to a small set that still containing most of the information that was available in the large set. A reduced set is much easier to analyze and interpret[10]. The image after fusion contains the property of high spatial resolution and high spectral resolution image of the original image, reserve the high frequency of the original image[11].

3.1.2 IHS Transform based Fusion Method

Intensity Hue Saturation (IHS) transform method used for enhancing the spatial resolution of multispectral (MS) images with panchromatic (PAN) images. It is capable of quickly merging the massive volumes of data by requiring only resampled MS data. Particularly for those users, not familiar with spatial filtering, IHS can profitably offer a satisfactory fused product[12]. Using PCA and IHS transform method for the fusion experiment, and programming in Matlab , fusion algorithms can be achieved.

3.1.3 Brovey Transform based Fusion Method

Brovey Transform (BT) is the widely used image fusion method based on chromaticity transform and RGB space transform. It is a simple and efficient technique for fusing remotely sensed images. The fusion algorithm can be seen in equation (1)

$$B_{MB_i} = \frac{\sum_j \sum_k B_{low_{ijk}} \times B_{high_{jk}}}{\sum_{i=1}^{n} \sum_j \sum_k B_{low_{ijk}}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

From the above formula, B_{MB} is the fusion image, n is bands numbers, denominator denote the summation of the three ETM+ multi-spectral bands.

3.1.4 HPF based Fusion Method

HPF used to obtain the enhanced spatial resolution multispectral image in which high-resolution images converted from space domain to frequency domain by using Fourier transform, and then to make the Fourier transformed image high-pass filtered by using a high-pass filter [13]. And make the high-pass filtered image added to multi-spectral image data. The fusion algorithm can be seen in equation (2)

$$F_k(i,j) = M_k(i,j) + HPF(i,j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

From the above formula $F_k(i,j)$ is the fusion value of the band k pixel$^{(i,j)}$, $M_k(i,j)$ the value of multi-spectral of band k pixel$^{(i,j)}$, $HPF(i,j)$ show the high frequency information of the high-resolution panchromatic image.

3.1.5 ML Transform based Fusion Method

In order to improve the quality of spatial and spectral information ML(Multiplication) transformation is a simple multiplication fusion method. Its fused image can reflect the mixed message of low-resolution images and high-resolution images [14]. The fusion algorithm can be seen in equation(3)

$$ML_{ijk} = \left(XS_{ijk} \times PN_{ij}\right)^{\frac{1}{2}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

From the above formula ML_{ijk} is the fusion image pixel value, XS_{ijk} is the pixel value of multi-spctral image , PN_{ij} is the pixel value of panchromatic.

3.1.6 SFIM based Fusion Method

SFIM fusion is the Smoothing Filter-based Intensity Modulation. SFIM is spatial domain fusion method based on smoothing lowpass filters[15].The fusion algorithm can be seen in equation (4)

$$B_{SFIM_i} = \sum_j \sum_k \frac{B_{low_{ijk}} \times B_{high_{jk}}}{B_{mean_{jk}}}, i = 1,2,3 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

From the above formula B_{SFIM} is the fusion image, I is the band value, j and k is the value of row and line. B_{low} is the low-resolution images, denote the multi-spectral band of ETM+. B_{high} is the high-resolution images, which is the panchromatic bands of ETM+, B_{mean} is simulate low-resolution images, which can be obtained by low-pass filter with the pan-band.

3.2 Fusion Image Evaluation Parameters

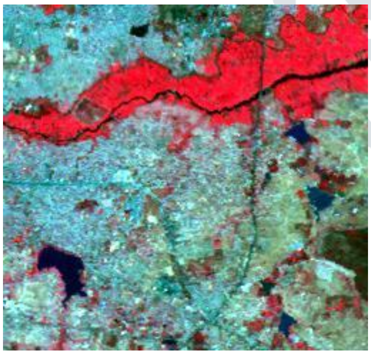
There are some commonly used image fusion quality evaluation parameters like the mean, standard deviation, average gradient, information entropy, and the correlation coefficient.

4. Results and Discussions

Erdas Model module and matlab are used for Programming the various fusion algorithm fused images are displayed: 5, 4 and 3 bands in accordance with the R, G, B, fusion results are shown as follows(figure1-6):

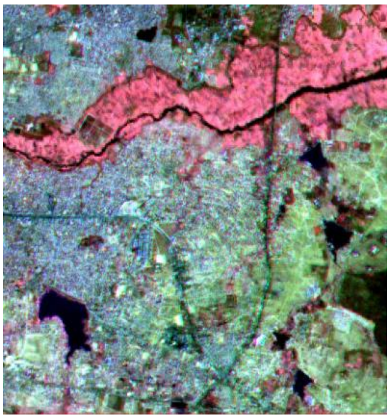
An example is designed, shown in Fig. 1 to explore different performances between fused methods.

a

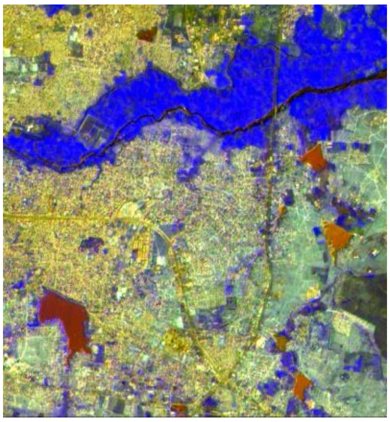


b

c



d



e

f

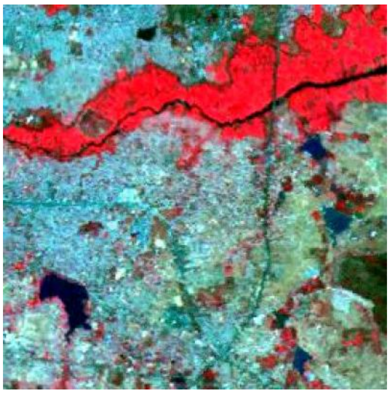


Fig.1. Example 1: (a) and (b) are images to be fused; (c) fused image using PCA; (d) fused image using Brovey Transform; (e) fused image using ML transform; (f) and SFIM fused image with 543bands .

4.1 Evaluation Parameters Statistics of Fused Image

The original Multi-Spectral images using XS to replace, and Panchromatic images with PAN replaced, evaluate parameters are shown in the Table3:

From the Evaluating Parameters Table 3, we observe see that

a. All fusion method in(average gradient) accordance with the definition in ascending order, HPF<HIS<SFIM<ML Transform< Brovey Transform<PCA

b. All fusion method in accordance with the entropy in ascending order, Brovey Transform<ML<SFIM<HPF<IHS<PCA

Table 3. Table for Evaluating Parameters

Image	Band	Mean	Standard deviation	Entropy	Correlation Coefficient with XS Image	Average Gradient	Correlation Coefficient with panchromatic Image
XS image	5 4 3	75.174 71.893 66.219	21.643 15.592 18.675	6.0949 6.0623 6.0594	1 1 1	4.0169 2.8164 3.2768	0.6536 0.7278 0.1658
PCA fused image	5 4 3	135.821 133.912 136.869	27.981 12.698 17.566	6.8675 6.8945 5.8345	0.6131 0.8676 0.2187	10.2324 9.2891 9.5892	0.9213 0.7564 0.9675
IHS fused image	5 4 3	72.978 71.653 63.858	14.742 22.678 21.386	5.8925 6.3745 5.8674	0.8083 0.8689 0.8089	6.4987 6.7985 6.4897	0.8912 0.6778 0.4813
Brovey Fused image	5 4 3	47.879 47.936 40.897	15.896 20.675 9.457	5.5346 6.0434 5.1218	0.7798 0.9549 0.7786	9.9123 9.1797 9.2589	0.9473 0.6612 0.7178
HPF fused image	5 4 3	75.109 71.868 66.148	21.841 15.251 20.879	6.2937 6.2792 6.2864	0.9355 0.9589 0.9786	6.5978 6.5012 5.6034	0.7187 0.7910 0.2897
ML fused image	5 4 3	99.788 97.897 92.953	22.897 18.974 18.967	6.1238 6.2478 5.989	0.9198 0.9381 0.8389	8.0967 7.5674 7.8971	0.8823 0.9015 0.6623
SFIM fused image	5 4 3	74.869 70.981 64.985	22.654 16.816 18.938	6.2678 6.1899 6.1789	0.9498 0.9567 0.9487	8.0512 7.2781 7.1878	0.7289 0.7908 0.3078

4.2 Fused Image Feature Identification Accuracy

Different fusion methods shows different impacts on image. Image identification is the application of spectral characteristics and structural characteristics of different characteristics to identify information; therefore spectra and texture information on the objectives of the interpretation are important significance [16]. Image classification is to label the pixels in the image with meaningful information of the real world. Classification of complex structures from high resolution imagery causes obstacles due to their spectral and spatial heterogeneity.

4.2.1 Classification Research Methods

Classification of complex structures from high resolution imagery causes obstacles due to their spectral and spatial heterogeneity[17]. The fused images obtained by different fusion techniques alter the spectral content of the original images. Make classification with maximum likelihood classification, using random method to select ground inspection points, to make accuracy test for maps of XS image and fused image, obtain total accuracy and Kappa index..

4.2.2 Accuracy Evaluation test for Unsupervised classification.

Unsupervised statistical clustering algorithms used to select spectral classes inherent to the data, more computer automated i.e. Posterior Decision. From the Table 4, below we find that PCA fused image has the worst spectrum distortion, and it leads to the lower classification accuracy. Ascending order of the classification accuracy is: PCA<IHS<XS<Brovey Transform<ML<HPF<SFIM.

Table 4. Image Unsupervised classification accuracy with comparative data

Type	XS image	PCA fused image	IHS fused image	Brovey fused image	ML fused image	HPF fused image	SFIM fused image
Overall Accuracy	76.49%	67.87%	76.26%	78.48%	80.38%	81.18%	84.34%
Kappa Index	0.6699	0.5267	0.6436	0.6802	0.7276	0.7457	0.77920

.

4.2.3 Accuracy Evaluation test for Supervised classification

Supervised image analyst supervises the selection of spectral classes that represent patterns or land cover features that the analyst can recognize i.e. Prior Decision. Supervised classification is much more accurate for mapping classes, but depends heavily on the cognition and skills of the image specialist. Apply supervised classification on original image and the SFIM based fusion image choosing 5,4,3 bands after the optimum bands selection, and evaluate the accuracy of the image classification, the accuracy of the classification results are showed in Table 5.

Table 5.Image supervised classification accuracy with comparative data

Type	XS image	SFIM based fusion image
Overall Accuracy	82.73%	89.16%
Kappa index	0.7657	0.8581

From the above Table 5 the total accuracy and Kappa index of the two, we observe that, the accuracy and Kappa index of the supervised classification of SFIM based fusion image are much higher than the XS images.

By comparing the Unsupervised classification and Supervised classification, we observe that the character of the above algorithms, on the basis of ETM+ classification, select SFIM fusion image as the basic image, PCA, ML fusion image has high integration of high frequency information, which has a certain value in the extraction of the internal structure of more dense area. HPF fusion image owing to the better spectral fidelity and more high-frequency information can be used as the auxiliary image of the visual interpretation, Brovey fusion image as the small information leading to the lower classification accuracy.

5. Conclusions And Future Work

This paper confers the analysis of image fusion methods and the quantitative evaluation using the parameters like mean, standard deviation, correlation coefficient, entropy, the average gradients and so on. Image fusion analysis with the panchromatic image and multispectral images in the same satellite system of Landsat-7 ETM+, as different types of sensors have different data types, it should be more complex in the process of fusion and the evaluation. However, it is necessary to analyze and to investigate more thoroughly. The study can be extended further by implementing object-oriented classification methods to produce more accurate results than the existing traditional pixel based techniques of unsupervised and supervised classification. It was ascertained that the SFIM image fusion method has better performance than other methods.

REFERENCES:

[1] Aditya Vailaya, Mário A. T. Figueiredo, Anil K. Jain and Hong-Jiang Zhang, Image classification for content-based indexing: *IEEE Transactions on Image Processing*, Vol. 10, Issue 1, 2001,117-130.

[2] Arnaud Martin and Christophe Osswald, Human expert fusion for image classification: *An International Journal of Information & Security*, Vol. 20, 2006, 122-143.

[3] René R. Colditz; Thilo Wehrmann; Martin Bachmann; Klaus Steinnocher; Michael Schmidt; Günter Strunz; Stefan Dech, Influence of image fusion approaches on classification accuracy: *International Journal of Remote Sensing*, Vol. 27, Issue 15, 2006, 3311 – 3335.

[4] Xu Hanqiu. Study on Data Fusion and Classification of Landsat 7 ETM + Imagery: *Journal of Remote Sensing*, Vol. 9, Issue 2, 2005,186-194.

[5] Teoh Chin CHUANG, Shattri MANSOR, Abdul Rashid Mohamed SHARIFF and Noordin AHMAD, Optimum Band Selection for Image Visualization of Multispectral Data in Relation to Natural Resources Management: *2nd FIG Regional Conference Marrakech, Morocco*, December 2-5, 2003.

[6]. Barbara Zitova, Jan Flusser, Image registration methods: *Image and Vision Computing*, Vol. 21, 2003, 977–1000.

[7] Anne H. Schistad Solberg, Torfinn Taxt and Ani1 K. Jain, **A** Markov Random Field Model for Classification of Multisource Satellite Imagery: *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 34, Issue 1, 1996, 100-113.

[8] Smara Y,Belhandj-Aissa A, and Sansal B.Multisources ERS-1 and Optical Data for Vegetal Cover Assessment and Monitoring in a semi-arid Region of Algeria: *International Journal of Remote Sensing*, Vol. 19, Issue 18, 1998, 3551-3568.

[9] Yang Jinghui*, Zhang Jixian, Li Haitao, Sun Yushan, Pu Pengxian, Pixel Level Fusion Methods For Remote Sensing Iimages: *ISPRS TC VII Symposium, ISPRS, IAPRS*, Vol. XXXVIII, Part 7B July 5–7, 2010.

[10] Kumar, S. Senthil; Muttan, S., PCA-based image fusion: Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XII, *Proceedings of the SPIE*, Vol. 6233, 2006.

[11] Wu Wenbo,Yao Jing∗,Kang Tingjun, Study of Remote Sensing Image Fusion and its Application in Image Classification: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. Vol. XXXVII. Part B7, 2008

[12] Te-Ming Tu, Huang P.S, Chung-Ling Hung and Chien-Ping Chang, A fast intensity-hue-saturation fusion technique with spectral adjustment for IKONOS imagery: *IEEE, Geoscience and Remote Sensing Letters*, Vol. 1, Issue 4, 309-312.

[13] X. Q. Ban, Comparison and Analysis on Remote Sensing Data Fusing Methods-A Case of Kaifeng Region Image, 2005, 2-4.

[14] Jinliang Wang, Chengna Wang and Xiaohua Wang, An Experimental Research on Fusion Algorithms of ETM+ image: *International Conference on Geoinformatics*, 2010, 1-6.

[15] J. G. Liu, Evaluation of Landsat-7 ETM+ Panchromatic band for image fusion with Multispectral bands: *Natural Resources Research*. Vol. 9, Issue 4, 2000, 269-276.

[16] Pan Xueqin, The comparison and analysis of data fusion of remote sensing image.Kaifeng: Henan university.

[17] H.R. Matinfar, F. Sarmadian, S.K. Alavi Panah and R.J. Heck, Comparisons of Object-Oriented and Pixel-Based Classification of Land Use/Land Cover Types Based on Lansadsat7, Etm+ Spectral Bands (Case Study: Arid Region of Iran): *American-Eurasian J. Agric. & Environ. Sci.*, Vol. 2, Issue 4, 2007: 448-456.