COMPARATIVE ANALYSIS THE EFFECT OF FUSION ALGORITHM ON HIGH RESOLUTION IMAGES

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Abstrac

Images fusion has been widely applied to imaging sensors for the purpose of resolution merge, image integration, and multi sensor data fusion. In image fusion, a low spatial resolution multispectral image is fused with a higher resolution panchromatic image to produce an image with higher spectral and spatial resolution. In this paper, we investigate the existing fusion methods based on visual ,spectral analyse and classification acuracy. The accuracy of classification result is assessed by means of the support vector machine based on radial basis function kernel. Comparing the performance of various fusion methods, it is shown that the Gram-Schmidt (GS) method yields the best accuracy, followed by the principal component analysis (PCA). The producer's and user's accuracies of the GS method are 91.8% and 91.1%, respectively, followed by 90.8% and 90.0% of the PCA method.

Keywords: image fusion, high resolution,classification, support vector machines

Abstrak

Fusi citra telah banyak diterapkan untuk berbagai keperluan salah satunya digunakan untuk penggabungan dua buah citra atau lebih baik dengan menggunakan data fusi multi sensor. Penggabungan citra fusi dilakukan dengan menyatukan citra yang mempunyai resolusi rendah (multispektral) dengan citra spasial yang beresolusi tinggi (pankromatik). Pada penelitian ini dilakukan pengujian dan analisis citra satelit dengan menggunakan berbagai metode fusi untuk menentukan kualitas suatu citra secara visual , spekral dan akurasi klasifikasi . Teknik klasifikasi citra fusi menggunakan metode Support Vector Machines (SVMs).

1. Indroduction

The recent increase in earth-observing satellites has led to more availability of high resolution images of various types from remote sensing. Multi sensor data fusion has become a discipline to which more and more optimum solutions are needed for a number of application cases [1]. The technique has become a very important issue for various remote sensing problems such as land classification, change detection, object identification, image segmentation, map updating, hazard monitoring, and visualization purposes. The technique of sensor fusion, or pan-sharpening, is employed to enhance the resolution of multispectral image in terms of the spatial information included in the Pan image (PAN). Pan-sharpening is also known as image fusion, resolution merge, image integration, or multi sensor data fusion [2-3]. When applied to an image, pan-sharpening is implemented on a pixel basis as illustrated in Figure1. In the fusion methods, so far many researchers have addressed the problem of multiresolution image fusion for remote-sensing applications, proposing different pan-sharpening methods [4]. Support vector machines (SVMs) based on radial basis function (RBF) kernel have been employed successfully in many fields, especially in remote sensing studies [5]. In this paper, we propose the generation of multispectral images (MS) with more information and better quality than original MIs by merging with PI, assessing the quality of resulting MS images using the SVM methodology In this paper, our motivation is to generate MS with more information and better quality than original MS by merging with PAN image. As pan-sharpening methods, here we apply IHS, CN-Brovey, PCA, GS, and CN-Spectral methods. The quality of resulting MS images was assessed with the correctness of the classification based on the SVMs based on radial basis function kernel.

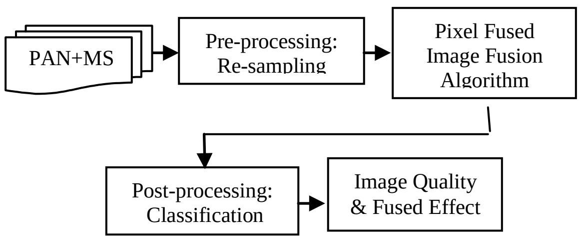

Fig. 1. Fusion Processing Flowchart

2. Data And Methodology

2.1 Study area and Remote sensing data set

The QuickBird data, consist of four multispectral bands and one Pan band, having a spatial resolution of 0.7 m and 2.8 m at nadir, respectively. The data location is the Sundarbans area (88°20’27.84”E, 22°32’45.67”N), India, obtained in November 2004 and distributed in the Global Land Cover Facility (http://glcf.umiacs.umd.edu/index.shtml). The panchromatic sensor collects information at the visible and near infrared wavelengths and has a bandwidth of 0.45-0.90 µm. The area covered in this imagery is mainly an urban area with a structured road, water, roof, tree, shadow and grass.

2.2 Pre-Processing

The most important prerequisite for accurate and performing fusion data is precise geometric correction. QuickBird image has been geometrically corrected and registered to WGS 84 datum with the Universal Transverse Mercator (UTM) zone 55S projection. A QuickBird are come from the same sensor at the same time, it easy to fuse them directly without registering and a thorny issue of registration was avoided . Next, in order the same pixel size PAN and MS images were fused to produce pan-sharpened multispectral images with 0.7 spatial resolution using re-sampling techniques for original QuickBird images respectively (Figure 2).

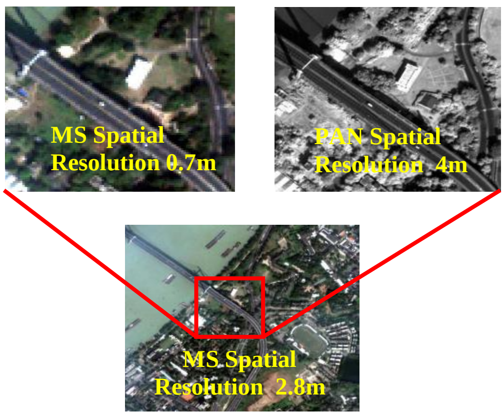

Fig.2. The re-sampling of pixel level for QuickBird data

A re-sampling is a process in which each data point (pixel) in the base map coordinate system is assigned a value (intensity, gray value, etc) based on the grey value of local images pixel. In re-sampling process, we are used to the nearest neighbor techniques.

2.3 Fusion Algorithm

In this study, data fusion is performed on a pixel basis using the algorithm of Gram-Schmidt, Ehler, modified intensity-hue-saturation (IHS), high pass filter, and wavelet- principal component analysis (PCA) [6-12].

- *Intensity, Hue and Saturation (IHS, Hue Saturation Value)*

The IHS fusion algorithm is widely used in image fusion to exploit the complementary nature of MS images. Three bands of a multispectral image form a colour image. The HIS fusion method converts a colour image from the red, green, and blue (RGB) space into the IHS colour space. Then the intensity band (I) in the IHS space is replaced by a high-resolution Pan image and then transformed back into the original RGB space together with the previous hue band (H) and the saturation band (S), resulting in an IHS fused image.

- *Color Normalized (CN) Brovey*

Generally, the Brovey algorithm provides good spatial quality but poor spectral quality. In this method, each band in color image and high resolution data divided by the sum of the color bands.

- *Gram Scmidth (GS)*

In this algorithm the high resolution Pan band is simulated from the lower spatial resolution spectral bands. Then a GS transformation is performed on the simulated Pan band and the spectral bands, where the simulated Pan band is employed as the first band. The high spatial resolution Pan band is swapped with the first GS band. Finally, the inverse GS transformation is then applied to form the pan-sharpened spectral bands .

- *Principal Component Analysis (PCA)*

The PCA algorithm belongs to the projection and substitution method categories. In this method, correlated variables are transformed into a set of uncorrelated variables called principal components. After the application of PCA to the original image, the first principle component (PC) image is replaced by the Pan image. Here it is assumed that the first PC image with the highest variance contains the most amount of information from the original image and will be the ideal choice to replace the high spatial resolution Pan image .

- *Color Normalized (CN) Spectral*

This algorithm can be used to simultaneously sharpen any number of bands, retaining the input image's original data type and dynamic range. Input multispectral bands are sharpened only if they fall within the spectral range of one of the fusion image's bands. The spectral range of the Pan is defined by the band center wavelength and full width-half maximum (FWHM) value, both obtained from the Pan image. Multispectral bands are grouped into spectral segments defined by the spectral range of the Pan band. Each multispectral band is multiplied by the Pan band, then normalized.

2.4 SVMs Classifier

To classify a pan-sharpened image, here we employ the RBF kernel, since it has been widely used in the literature in land classification [13-14]and change detection studies with various satellite data. The RBF function is expressed as

$$K(x_i, x_j) = \exp\left(-\gamma \left\| x_i \cdot x_j \right\|\right) \qquad (1)$$

where x_i and x_j represent a set of training data, $K(x_i, x_j)$ is kernel function and γ is a user-defined parameter.

2.4 Spectral quality assessment

The goal of image quality assessment is to supply quality metrics that can predict perceived image quality automatically. In the following some metric were implemented to judge the performance of pan-sharpening methods as follows [6]:

- *Standard Deviation (STD)* is an important index to weight the information of image, it reflects the deviation degree of values relative to the mean of the image. The greater STD is, the more dispersible the distributing of the gray grade
- *Bias* is used to calculates correlation between the fused image and the original low spatial resolution image
- *Root mean squared error (RMSE*) calculates the average squared difference between the original multispectral and pan-sharpened image
- *Peak signal to signal noise ratio (PSNR***)** is used to reveals the radiometric distortion of the final image compared to the original.
- *Relative Dimensionless Global Error in Synthesis (ERGAS*) was proposed by Wald as a multi-modal index to characterize the quality of process and, presents the normalized average error of each band of processed image . Increasing in ERGAS index may be the result of degradation in images due to fusion process.

3. Result And Discussion

3.1 Performance comparison using visual assessment

Figure 3(a) show the MI of the QuickBird scene. The pan-sharpened images resulting from the five different image fusion methods are shown in Fig. 3(b)-(f), namely (b) HIS, (c) CN-Spectral, (d) CN-Brovey, (e) PCA and (f) GS Fusion. All fused images appear to be very close to the Pan image in terms of the spatial quality. Since vegetation pixels exhibit high reflectance in the near infrared band, it often happens that those pixels appear too bright (i.e., poor color recovery) when the intensity image is simply replaced by the Pan image. Among the results shown in Fig. 3(c)-(g), the IHS fused image (c) is relatively good in the sharpness but rather poor in the reproduction of the RGB color. In the CN-Brovey fused image (d), the color provides good contrast but the color balance is somewhat distorted. The color recovery PCA fused image (e) is much better than (c) or (d), but some mis-registration occurs around the bright object. The PCA algorithm is dependent on the scene content: for instance, high vegetation coverage causes poor performance due to the high near-infrared reflectance. The result of the GS image fusion (f) is quite similar to PCA, with good color preservation and image sharpness, Table 1.

(a) **(b)** **(c)**

(d) (e) (f)

Fig.3. Original and pan-sharpened images: (a) Original MS image, and (c)-(f) results of different pan-sharpening methods, (b) HIS,(c) CN-Spectral (d) CN-Brovey, (E) PCA, and (F) GS.

Table 1. Visual assessment for pixel fused color information

No	Methods	Color
1	IHS	Color distortion
2	CN-Spectral	Color distortion
3	CN-Brovey	Color distortion
4	PCA	Color preservation
5	GS	Color preservation

3.2 Performance comparison using spectral quality

A thorough performance comparison spectral quality of fused images, we have uses the following parameter such as mean, standard deviation), RMSE, PNSR, and ERGAS. The fused images which will best preserve the spectral information and higher the spectral quality when the mean and standard deviation value are closer to original MIs, the smallest error value of the RMSE and ERGAS, and the highest possible PSNR value. In Table 2, a general observation for all the methods in RGB colour bands compared. We can concluded that GS technique has preserve the spectral information and good a spectral quality and followed by PCA respectively.

Table 2. Comparison spectral quality assessment for different fused image

Fusion Algorithm	Statistical Assessment					
	Mean	STD	Bias	RMSE	PSNR	ERGAS
MS QuickBird	**198.66**	**28.66**	-	-	-	-
IHS	90.33	59	0.49	30.34	8.10	4.81
CN-Brovey	82	25.33	0.09	33.66	5.15	5.92
CN Spectral	235.66	44	-1.85	18.79	17.17	1.22
PCA	230.67	30.66	0.02	13.33	22.49	0.81
GS	**232**	**26.33**	**-0.004**	**4.33**	**42.51**	**0.28**

For the classification accuracy can be evaluated using the confusion matrix based on the classification result for the region of interest. Table 2 shows the overall accuracy, kappa coefficient, producer and user accuracies for the pan-sharpened images obtained with the five algorithm. The SVMs with RBF are applied to achieve accurate classification of spectral images, assuming the following seven categories: sea, shadow, bare soil, tree, pastures, bridge/road, and building/roof. A high overall accuracy of 89.59% has been attained for the PCA fused image, followed by GS (85.59%), CN-Spectral (87.738%), IHS (86.78%) and CN-Brovey (83.74%). A large Kappa coefficients of 0.88 and 0.87 are obtained for both GS and PCA. Both the user's producer's accuracies are higher for both GS and PCA, as compared with other fusion algorihm. The producer's and user's accuracies of the GS method are 91.8% and 91.1%, respectively, followed by 90.8% and 90.0% of the PCA method.

Table 3. Classification accuracy for difference fused image

Cerrado Class (%)	Fusion Algorithm				
	IHS	CN-Brovey	CN-Spectral	PCA	GS
Overall accuracy	86.78	83.74	87.73	89.59	85.59
Kappa coefficient	0.83	0.79	0.84	0.87	0.88
Producer's accuracy	86.55	82.35	87.63	90.84	91.8
User's accuracy	85.52	81.93	88.65	89.99	91.11

4. Conclusion

We have compared several five pan-sharpening methods for implementing image fusion. The visual as well as spectral analyses of the fused images indicate that the results generated with GS and PCA methods preserve spectral and spatial information of the objects in original images better than the results generated by IHS, CN-Brovey and CN-Spectral methods. In addition, comparison of statistical indicators also shows the superiority of the GS and PCA methods. The classification of the pan-sharpened QuickBird test image is achieved by means of the SVMs, and the accuracy of classification reveals that the images based on GS and PCA yield best accuracies.

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5. References

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