

Improvement Of Image Quality By Using Image Fusion Techniques

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Abstract: Image processing techniques primarily focus upon enhancing the quality of an image or a set of images and to derive the maximum information from them. Image Fusion is such a technique of producing a superior quality image from a set of available images. It is the process of combining relevant information from two or more images into a single image wherein the resulting image will be more informative and complete than any of the input images. Fusion Methods combines a low-resolution color multispectral image with a high-resolution grayscale panchromatic image to create a high-resolution fused color image. In this paper we examine five different Fusion Methods: Brovey Transform, IHS, PCA, Wavelet fusion, “Mallat” algorithm, and VWP and evaluate their effectiveness. Additionally, we propose an extension to the IHS Fusion Methods method to improve the resulting spectral quality. In order to compare the method results we evaluate spatial and spectral qualities by relying on both visual inspection and metric performance data. Our results indicate that VWP is most effective in preserving spectral data, while IHS methods produce images with the best spatial quality.

IndexTerms—Fusion, pan sharpening, quality assessment, very high resolution satellites.

1. INTRODUCTION

With the recent rapid developments in the field of sensing technologies multi-sensor systems have become a reality in a growing number of fields such as remote sensing, medical imaging, machine vision and the military applications for which they were first developed. The result of the use of these techniques is a great increase of the amount of data available. Image fusion provides an effective way of reducing this increasing volume of information while at the same time extracting all the useful information from the source images rapidly. Multi-sensor data often presents complementary information about the region surveyed, so image fusion provides an effective method to enable comparison and analysis of such data. The aim of image fusion, apart from reducing the amount of data, is to create new images that are more suitable for the purposes of human/machine perception, and for further image-processing tasks such as segmentation, object detection or target recognition in applications such as remote sensing and medical imaging. For example, visible-band and infrared images may be fused to aid pilots landing aircraft in poor visibility.

Multi-sensor images often have different geometric representations, which have to be transformed to a common representation for fusion. This representation should retain the best resolution of either sensor. A prerequisite for successful in image fusion is the alignment of multi-sensor images. Multi-sensor registration is also affected by the differences in the sensor images.

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Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. The fusion of images is often required for images acquired from different instrument modalities or capture techniques of the same scene or objects (like multi-sensor, multi-focus and multi-modal images). Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. Image fusion can synthesize many images from different sensors into a picture which can meet specific application by using a mathematical model. It can effectively combine the advantages from different images and improve the analysis ability. For example, in multi-focus imaging one or more objects may be in-focus in a particular image, while other objects in the scene may be in focus in other images.

2. PREVIOUS WORK

The primitive fusion schemes perform the fusion right on the source images. This would include operations like averaging, addition, subtraction/omission of the pixel intensities of the input images to be fused. These methods

often have serious side effects such as reducing the contrast of the image as a whole. But these methods do prove good for certain particular cases wherein the input images have an overall high brightness and high contrast.

3. PROBLEM DEFINITION

The launch of high-resolution satellites used for remote sensing has created a need for the development of efficient and accurate image fusion methods. These satellites are commonly capable of producing two different types of images: a low-resolution multispectral image and a high-resolution panchromatic image. The multispectral sensor provides multi-band images with accurate color data with low spatial resolution. Conversely, the panchromatic sensor yields grayscale images with high spatial resolution but imprecise color data. There are a number of applications in remote sensing that require images with both high spatial and spectral resolutions. The fusion of the multispectral and panchromatic images, or *pan-sharpening*, provides a solution to this by combining the clear geometric features of the panchromatic image and the color information of the multispectral image. In this paper we will examine different Fusion happening techniques and explore various metrics that can be used to judge the image quality of the fused image. The satellite has four bands: red, green, blue and infrared. The most common fusion-sharpening techniques are the Intensity-Hue-Saturation Technique (IHS), the wavelet method, and principal component analysis (PCA). In this paper, we also compare these three methods to other advanced fusion sharpening methods such as *Brovay Transform*, "*Mallat*" algorithm, and Variation Wavelet Pan-sharpening (VWP).

4. MOTIVATION

The motivation behind the idea is that the fusion of images is often required for images acquired from different instrument modalities or capture techniques of the same scene or objects (like multi-sensor, multi-focus and multi-modal images).

5. PROPOSED METHODS

Image fusion is the process that combines information from multiple images of the same scene. These images may be captured from different sensors, acquired at different times, or having different spatial and spectral characteristics. The object of the image fusion is to retain the most desirable characteristics of each image. With the availability of multisensory data in many fields, image fusion has been receiving increasing attention in the researches for a wide spectrum of applications. We use the following four examples to illustrate the purpose of image fusion.

IHS Transformation Technique

IHS (Intensity-Hue-Saturation) is the most common image fusion technique for remote sensing applications and is

used in commercial pan-sharpening software. This technique converts a color image from *RGB* space to the *IHS* color space. Here the *I* (intensity) band is replaced by the panchromatic image. Before fusing the images, the multispectral and the panchromatic image are histogram matched. The image is converted to *IHS* color space using the following linear transformation:

$$\begin{bmatrix} I \\ v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ -\sqrt{2} & -\sqrt{2} & 2\sqrt{2} \\ \frac{1}{6} & \frac{-1}{6} & \frac{2}{6} \\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} & 0 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

Therefore the entire fusion process can be expressed mathematically as

$$\begin{bmatrix} F(R) \\ F(G) \\ F(B) \end{bmatrix} = \begin{bmatrix} 1 & -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -1 & -1 \\ 1 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & \frac{1}{\sqrt{2}} & 0 \end{bmatrix} \begin{bmatrix} Pan \\ v_1 \\ v_2 \end{bmatrix}$$

This process is equivalent to

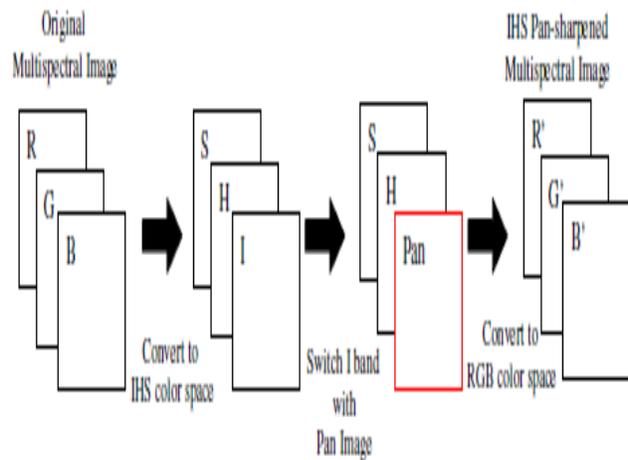


Fig.1. IHS Transformation Technique

Implementing the IHS fusion method in this manner is very efficient and is called the fast HIS technique (FIHS), making IHS ideal for the large volumes of data produced by satellites. Ideally the fused image would have a higher resolution and sharper edges than the original color image without additional changes to the spectral data. However, because the panchromatic image was not created from the same wavelengths of light as the RGB image, this technique produces a fused image with some color distortion from the original multispectral. This problem becomes worse the more the intensity band and panchromatic image differ. There have been various modifications to the FIHS method in an attempt to fix this

problem. One of the first modifications of the FIHS method extends the IHS method from three bands to four by incorporating an infrared component (Tu *et al.*, 2005). Because the panchromatic image sensors pick up infrared light (IR) in addition to visible wavelengths, this modification allowed the calculated intensity of the multispectral image to better match the panchromatic image, thus causing less color distortion in the final fused image. A similar modification called the FIHS-SA method uses four bands but incorporates weighting coefficients on the green and blue bands in an attempt to minimize the difference between *I* and the panchromatic image. In order to minimize spectral distortion in the IHS pan-sharpened image, we propose a new modification of IHS that varies the manner the intensity band is calculated depending on the initial multispectral and panchromatic images. To minimize spectral distortion the intensity band should approximate the panchromatic image as closely as possible. Therefore in this Adaptive IHS method we want to determine the non-negative coefficients α_i 's that best approximate

$$I = \alpha_1 M_1 + \alpha_2 M_2 + \alpha_3 M_3 + \alpha_4 M_4 \approx pan$$

In order to calculate these coefficients we create the following function *F* to minimize with

$$F(\alpha) = \sum_x \left(\sum_i (\alpha_i M_i(x) - P(x)) + \gamma \sum_i (\max(0, -\alpha_i)^2) \right)$$

The first term ensures that the coefficients yield a linear combination that approximates the panchromatic image. The second term enforces the non-negativity constraint on the α_i 's using the Lagrange multiplier γ . In order to solve this minimization problem we use a semi-implicit gradient descent method, to which Michael Moeller contributed.

PCA (Principal Component Analysis)

In the PCA-based method, the PCA transform converts inter correlated multispectral bands into a new set of uncorrelated components. 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 panchromatic image. All the other multispectral bands are unaltered. An inverse PCA transform is performed on the modified panchromatic and multispectral images to obtain a high-resolution pan-sharpened image.

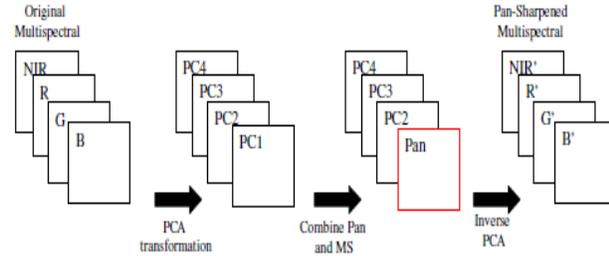


Fig.2. Principal Component Analysis

Mallat algorithm

“Mallat” algorithm (Mallat) is based on a multiresolution dyadic scheme that allows decomposing an image into an approximation image and three wavelet coefficient images which retain the horizontal, vertical, and diagonal details, respectively, that are lost between two consecutive approximations. The computation is accomplished with a pyramidal scheme based on convolutions followed by a decimation operation. Finally, the process is inverted, and the MS fused image can be reconstructed from the MS approximation image and the PAN wavelet coefficients.

Wavelet

The wavelet fusion method is based on the wavelet decomposition of images into different components based on their local frequency content. We perform the Discrete Wavelet Transforms (DWT) on the multispectral and panchromatic images to extract the low frequency data from the multispectral image and the high frequency data from the panchromatic image. These components are combined to create the Fused Wavelet Coefficient Map. The inverse wavelet transformation is performed on the fused map to create the final pan-sharpened image. Below is a visual representation of the wavelet method.

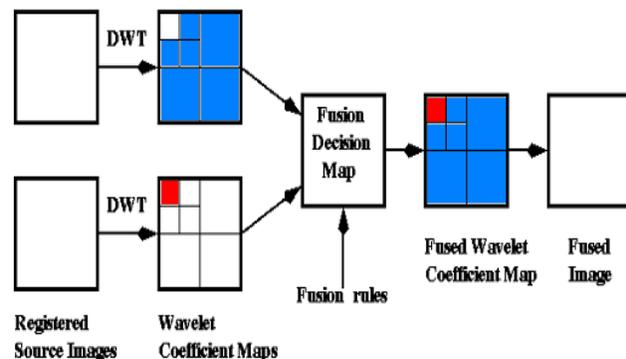


Fig.3. Wavelet Analysis

VWP (Variational Wavelet Pan-sharpening)

The pan-sharpening method VWP combines the Wavelet and minimizing energy functional methods. It uses the wavelet coefficients in order to get higher spectral quality and uses the energy functional of to produce clear edges. VWP explicitly preserves spectral quality better. Also,

unlike the minimizing energy functional, the VWP does not approximate the panchromatic image as a linear combination of the multispectral bands. This is beneficial because it does not limit the method to four band images

6. METRICS PERFORMANCE EVALUATION

There are many different ways to analyze the results of pan-sharpened images and compare different methods. When comparing different methods, we are interested in spatial and spectral quality. In judging spatial quality, it is much easier to see the sharpness of the edges. But when judging spectral quality, it is much more difficult to match the colors of the final result to the original multispectral by visual inspection. There are many metrics that analyze the spectral quality.

- RMSE- Root Mean Square Error
- RASE- Relative Average Spectral Error
- ERGAS- Relative Dimensionless Global Error in Synthesis
- CC- Correlation Coefficient
- SID- Spectral Information Divergence
- SAM- Spectral Angle Mapper
- Q average - A Universal Image Quality Index

Relative dimensionless global error in synthesis (ERGAS) calculates the amount of spectral distortion in the image. The formula for ERGAS is given by

$$ERGAS = 100 \frac{h}{l} \sqrt{\frac{1}{N} \sum_{n=1}^N \left(\frac{RMSE(n)}{\mu(n)} \right)^2}$$

where $\frac{h}{l}$ is the ratio between pixel sizes of Pan and MS, $\mu(n)$ is the mean of the nth band, and N is the number of bands.

Spectral Angle Mapper (SAM) compares each pixel in the image with every endmember for each class and assigns a value between 0 (low resemblance) and 1 (high resemblance). The formula for SAM at a specific pixel is given by

$$\text{Cos}\alpha = \frac{\sum_{i=1}^N A_i B_i}{\sqrt{\sum_{i=1}^N A_i A_i} \sqrt{\sum_{i=1}^N B_i B_i}}$$

Spectral Information Divergence (SID) is derived from the concept of divergence arising in information theory and can be used to describe the statistic of a spectrum. It also views each pixel spectrum as a random variable and then measures the discrepancy of probabilistic behaviors between spectra. To compute SID, we have the vector $x = (x_1, \dots, x_N)^T$, which is taken from the multispectral image and $y = (y_1, \dots, y_N)^T$ which is a vector from the final fused image. The range of x_i 's and y_i 's needs to be between [0, 1] and we define this by

$$SID(x, y) = D(x||y) + D(y||x)$$

A Universal Image Quality Index (Q-average) models any distortion as a combination of three different factors: loss of correlation, luminance distortion, and contrast distortion.

$$Q = \frac{4\sigma_{xy}\bar{x}\bar{y}}{(\sigma_x^2 + \sigma_y^2)[(\bar{x})^2 + (\bar{y})^2]}$$

Each component of the formula can be defined as follows:

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i \quad \bar{y} = \frac{1}{N} \sum_{i=1}^N y_i$$

$$\sigma_x^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2$$

$$\sigma_y^2 = \frac{1}{N-1} \sum_{i=1}^N (y_i - \bar{y})^2$$

$$\sigma_{xy}^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})$$

The relative average spectral error (RASE) characterizes the average performance of the method of image fusion in the spectral bands

$$RASE = \frac{100}{M} \sqrt{\frac{1}{N} \sum_{i=1}^N RMSE^2(B_i)}$$

In the formula for RASE, M is the mean radiance of the N spectral bands (B_i) of the original MS bands.

Root Mean Squared Error (RMSE)

We also used root mean squared error (RMSE) and correlation coefficient (CC) to analyze and compare the spectral quality. The CC between the original MS image and the final fused image is defined as

$$RMSE = \sqrt{\frac{\sum_x \sum_y (A_i(x) - F_i(x))^2}{n \times m \times d}}$$

In this formula x is the pixel and (i) is the band number. Also n is the number of rows, m is the number of columns and d is the number of bands. We used all the metrics stated above to conclude which Fusion method performs best spectrally.

7. SIMULATION RESULTS

In comparing the spatial quality, as mentioned before, it is relatively easy to judge spatial quality just by looking at the image. For example, in Image 1, IHS and PCA demonstrate clear edges whereas Wavelet experiences what is called a stair-casing effect. Similarly for all the other images this pattern follows. In order to be more accurate we used the metric mentioned above to evaluate the images as well. In the results of the spatial metric, it confirms our prediction that IHS and PCA have the highest spatial quality, but it misleads the reader in evaluating Wavelet. Overall, in Table 1, which is the average of the results of the six images, it is clear the HIS and PCA perform best spatially. The spectral quality was more difficult to judge visually; therefore we used many metrics in order to evaluate the results. In all the fused images, IHS and PCA have the highest color distortion. This is due to overusing the panchromatic image. The colors visually look very different that the original MS. It is difficult

to say which of the other images match better to the MS. For example in Image 4 one can see the color of the swimming pool is very different in the IHS and PCA, but it's hard to conclude which of the other fused images has the best spectral quality. VWP seem to have the least spectral distortion, but it's difficult to conclude this visually. We ran the metrics on all the images and took an average of the results. Looking at table 1, we can conclude from the metrics that VWP performs best spectrally. In comparing the three IHS methods only, the metrics conclude the original IHS performs best spatially whereas the Adaptive IHS performs best spectrally. In conclusion, overall the VWP performs best spectrally and the IHS performs best spatially. There is always a tradeoff in spectral and spatial quality, because of this the choice of method can depend on the how the fused image will be used. Also given our metric results, we concluded that among the three different IHS methods, the Adaptive IHS performs best spectrally

Table:1. Image 1 Metrics Performance Evaluation

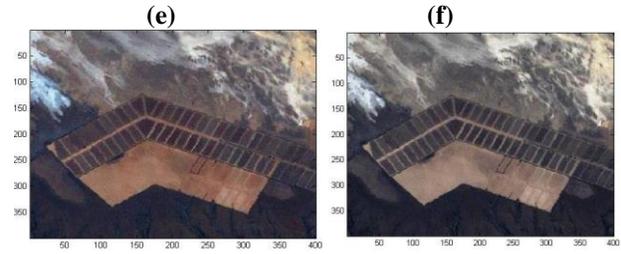
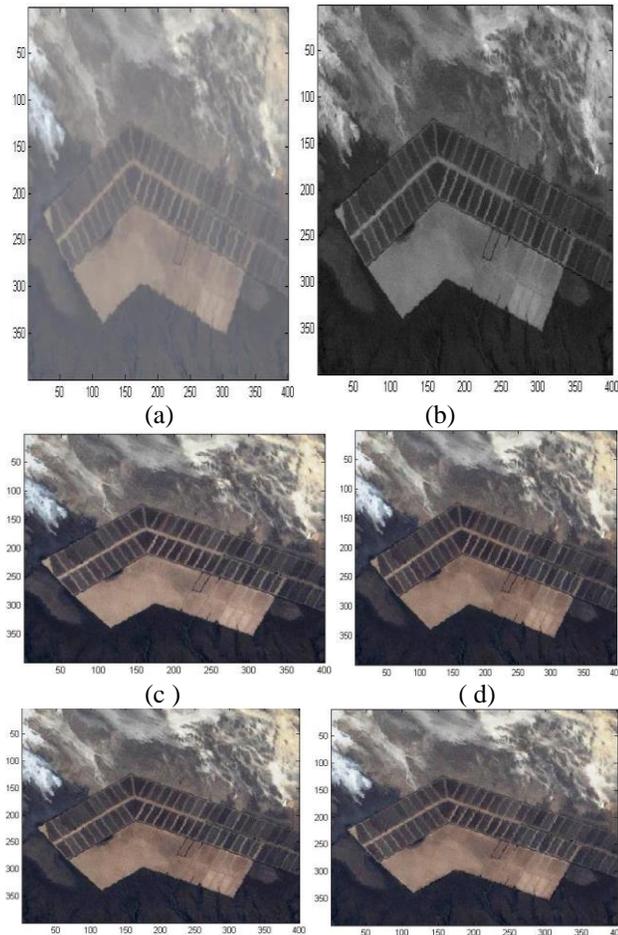


Fig. (a) Multispectral Image, (b) Panchromatic Image, (c) IHS, (d) Adaptive HIS, (e) IKONOS HIS (f) Wavelet (g) PCA, (h) Brovey

8. CONCLUSION

We have performed a detailed visual and quantitative analysis regarding the spatial and spectral distortions produced by some pan sharpening techniques. VWP

	CC	ERGAS	Q	RASE	RMSE	SAM	SI D	Spatial
IHS	0.0056	1.28	0.74	5.22	5.53	0.198	0.001	0.99
IKONOS IHS	0.0009	1.03	0.99	4.09	4.33	0.168	0.002	0.98
Adaptive IHS	0.0006	1.0045	0.998	4.04	4.27	0.049	0.001	0.968
Wavelet	0.0035	0.7725	0.99	3.08	3.26	0.054	0.002	0.95
PCA	0.11	2.57	0.98	10.38	10.98	0.046	0.007	0.934
VWP(Brovey)	0.006	12.46	0.085	33.67	35.63	2.28	0.003	0.99

performs the best spectrally. IHS based methods perform best spatially. The adaptive IHS method performs better spectrally than the original IHS and IKONOS IHS. There is a tradeoff in every method between the spatial and spectral resolution. The choice of method depends on how the fused image will be used. Finally, after applying the pan sharpening algorithms to real images having different types of land covers (agricultural, coastal, dunes, forest, water reservoir, urban, and vegetation), we can conclude that, in general, the spatial and spectral effectiveness of each algorithm does not depend on the specific image to be fused.

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