COMPARATIVE ANALYSIS OF IMAGE FUSION TECHNIQUES: A REVIEW

Ambika Aery *

Sonit Sukhraj Singh **

ABSTRACT

The image fusion came into existence with the rapid advancements in technology which merges images from multisource images to obtain new and improved image. However, all the physical and geometrical information required for detailed assessment might not available by analyzing the images separately. In multi-sensory images , there is a trade off between spatial and spectral resolutions resulting in image loss. Image fusion fuses two or more images and synthesizes them into one that contains all the significant or clear information from each input image. These images may be acquired from different sensors, or may be from the same scene with focus on different parts on it. So, the image fusion can be divided into pixel, feature and decision /symbol levels. The most commonly used image fusion techniques are: Principal Component Analysis(PCA),Intensity-Hue-Saturation (HIS) technique,High-pass filtering (HPF) technique and Wavelet Transform technique(WT). This paper presents detailed information and comparisons between the techniques used in image fusion.

* Department of Electronics and Communication Engineering, Lovely Professional University, Phagwara.

** Assistant Professor, Department of Electronics and Communication Engineering, Lovely Professional University, Phagwara.

I. INTRODUCTION

The term fusion is generally defined as an approach to extract the information which is acquired from several domains. In image fusion (IF), the objective is to combine corresponding multi-sensors, multi-view or multi-temporal information in order to obtain a good quality image which can lead the observers to some better decision. The meanings and the measurement of the quality of the fused image vary application to application. Image fusion has got immense importance in many application areas. In the fields of remote sensing and astronomy, to obtain high spatial and spectral resolutions, multi-sensor image fusion is performed where the sensors have high spatial and spectral resolutions respectively. In medical imaging, we find many fusion applications which simultaneously evaluate CT, MRI, and/or PET images. A number of applications using multi-sensor fusion of visible and infrared images have appeared in military, security, and surveillance areas. In case of multi-focus or multi-view image fusion techniques, the images of the same scene taken by the same sensor are fused to achieve an image in which all the objects are in focus. These fusion techniques usually generate an image with higher resolution than the resolution provided by the sensors. In multi-temporal image fusion applications, the images of the same scene are recorded at different times to keep track of different changes in the scene or to get a less degraded image of the scene. It is impossible to devise a universal method valid to all image fusion tasks. Every scheme should take into account not only the fusion reason and the characteristics of individual sensors, but also particular imaging conditions, imaging geometry, noise corruption, required accuracy and application-dependent data properties [1].

This paper concludes with some sections out of which, section II the basic principal and the method of image fusion, section III includes techniques used in image fusion , section IV includes the comparative analysis of techniques used in image fusion, section V includes the conclusion drawn from the paper.

II. BASIC PRINCIPAL & METHOD OF IMAGE FUSION

Remote sensing image fusion method can be attributed to the three-level fusion method, which is based on pixel-level fusion method, feature-level fusion method and decision level fusion methods [2]. Pixel level fusion (Pixels-based fusion) is the sensor does not make too many of the original information before the processing of information processing [3]. The advantage is to retain as much information, with the most accurate (such as the use of wavelet transform, HPF transformation, IHS transformation, etc.). Feature level fusion (Feature-based fusion) is the original information of the sensor pre-processing and feature extraction carried out after information processing, the extracted feature information should be sufficient that the amount of original information and full statistics, and then press features information on the classification of multiple information sources, gathering and synthesis [4]. The advantage is to achieve a significant compression of information is conducive to real-time processing, the integration gives the results of decision analysis to maximize the characteristics of the information required, its disadvantage is poor accuracy than the pixel level fusion. Decision level fusion (Decision level based fusion) is the highest level of integration, which is the pixel level and feature level fusion of information provided on the basis of various features, the image information to professional recognition, classification or target detection in access to the regional characteristics of the target state and other decision-making information, and then obtained the topic of image fusion processing [5]. The advantage is highly fault-tolerant, a good opening, processing time is short.

The fusion process is performed in three levels as mentioned above that are pixel-level, feature-level and decision-level is shown in figure 1. Figure 1, describes the different levels of image fusion.

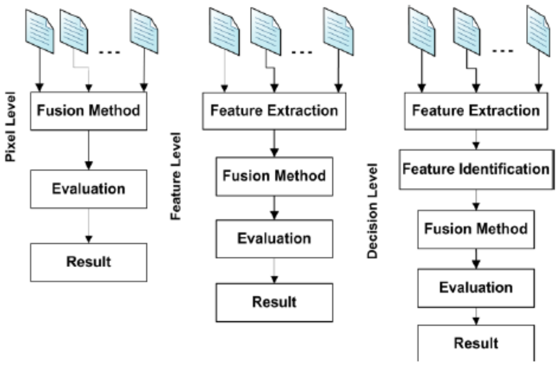

Figure 1: Image fusion level [2]

The basic meaning and requirements of image fusion are: (1) Image fusion should include techniques that can implement the geometric alignment of several images acquired by different sensors. Such techniques are called as multi-sensor image registration. (2) Image fusion must have a processing step that can segment the commonly interesting region of images. (3) Image fusion should solve the problem of extracting and describing the attributes or features of the concerned object (target or target region) in every interesting region of images. (4) Image fusion should be capable of fusing the information of attributes of interesting regions or/and the concerned objects and producing an image interpretation according to the applied requirements.

III. TECHNIQUES USED IN IMAGE FUSION

The image fusion techniques fall in two categories. In the first category, images are fused in spatial domain. In spatial domain, corresponding pixel values of the source images are operated using simple mathematical operators such as max, mean etc. and the fused image is generated. In this kind of fusion, some undesired effects such as blur are also introduced in the fused image which can mislead to the observer. To overcome these problems, in the second category, the source images are first transformed into another domain. Multi-scale transforms such as wavelets, Laplacian

pyramids, Morphological pyramids and gradient pyramids have been proposed in the second category of the image fusion techniques. Discrete wavelet transform provide directional information in decomposition levels and contain unique information at different resolutions.

In this paper we focus on four techniques used in image fusion that are principal component analysis (PCA), intensity-hue-saturation (HIS), high-pass filtering technique(HPF) and wavelet transform technique (WT) .

A. Intensity-Hue Saturation Technique

The IHS technique is a standard procedure in image fusion, with the major limitation that only three bands are involved [3]–[6]. Originally, it was based on the RGB true color space. It offers the advantage that the separate channels outline certain color properties, namely intensity (I), hue (H), and saturation (S). This specific color space is often chosen because the visual cognitive system of human beings tends to treat these three components as roughly orthogonal perceptual axes. However, in remote sensing, arbitrary bands are usually assigned to the RGB channels to produce false color composites for display purposes only. The IHS technique usually comprises four steps: 1) transform the red, green, and blue (RGB) channels (corresponding to three multispectral bands) to IHS components; 2)

match the histogram of the panchromatic image with the intensity component; 3) replace the intensity component with the stretched panchromatic image; and 4) inverse-transform HIS channels to RGB channels. The resultant color composite will then have a higher spatial resolution in terms of topographic texture information. The forward transform of this method is described by (10), while (11) describes the backward transformation. The original transformation matrix of the IHS transformation is orthogonal

$$\begin{bmatrix} \mathrm{DN}^{l}_{\mathrm{PAN}} \\ V1 \\ V2 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{-1}{\sqrt{6}} & \frac{-1}{\sqrt{6}} & \frac{2}{\sqrt{6}} \\ \frac{1}{\sqrt{6}} & \frac{-1}{\sqrt{6}} & 0 \end{bmatrix} \begin{bmatrix} \mathrm{DN}^{l}_{\mathrm{MS1}} \\ \mathrm{DN}^{l}_{\mathrm{MS2}} \\ \mathrm{DN}^{l}_{\mathrm{MS3}} \end{bmatrix} \qquad \text{-(1)}$$

and $H = \tan^{-1}[V2/V1], S = \sqrt{V1^2 + V2^2}$

$$\begin{bmatrix} \mathrm{DN}^{h}_{\mathrm{MS1}} \\ \mathrm{DN}^{h}_{\mathrm{MS2}} \\ \mathrm{DN}^{h}_{\mathrm{MS3}} \end{bmatrix} = \begin{bmatrix} 1 & \frac{-1}{\sqrt{6}} & \frac{3}{\sqrt{6}} \\ 1 & \frac{-1}{\sqrt{6}} & \frac{-3}{\sqrt{6}} \\ 1 & \frac{2}{\sqrt{6}} & 0 \end{bmatrix} \begin{bmatrix} \mathrm{DN}^{h'}_{\mathrm{PAN}} \\ V1 \\ V2 \end{bmatrix}$$ -(2)

Since the forward and backward transformations are both linear, replacing V1 and V2 in (1) by V1 and V2 from (2) yields the mathematical model of the generalized IHS method

$$\begin{bmatrix} \mathrm{DN}^{h}_{\mathrm{MS1}} \\ \mathrm{DN}^{h}_{\mathrm{MS2}} \\ \mathrm{DN}^{h}_{\mathrm{MS3}} \end{bmatrix} = \begin{bmatrix} \mathrm{DN}^{l}_{\mathrm{MS1}} \\ \mathrm{DN}^{l}_{\mathrm{MS2}} \\ \mathrm{DN}^{l}_{\mathrm{MS3}} \end{bmatrix} + \left(\mathrm{DN}^{h'}_{\mathrm{PAN}} - \mathrm{DN}^{l}_{\mathrm{PAN}}\right) \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

Where $\mathrm{DN}^{l}_{\mathrm{PAN}} = (1/3)(\mathrm{DN}^{l}_{\mathrm{MS1}} + \mathrm{DN}^{l}_{\mathrm{MS2}} + \mathrm{DN}^{l}_{\mathrm{MS3}})$ and $\mathrm{DN}^{h'}_{\mathrm{PAN}}$ is $\mathrm{DN}^{h}_{\mathrm{PAN}}$., stretched to have same mean and variance as $\mathrm{DN}^{l}_{\mathrm{PAN}}$.

B. Principal Component Analysis

The PCA method is similar to the IHS method, with the main advantage that an arbitrary number of bands can be used [10], [11]. The input LRMIs are first transformed into the same number of uncorrelated principal components. The first principal component image contains the information that is common to all the bands used as input to PCA, while the spectral information that is unique to any of the bands is mapped to the other components. Then, similar to the IHS method, the first principal component (PC1) is replaced by the HRPI, which is first stretched to have the same mean and variance as PC1. As a last step, the HRMIs are determined by performing the inverse PCA transform.

The mathematical models of the forward and backward processes are represented by (3) and (4). The transformation matrix contains the eigenvectors, ordered with respect to their eigenvalues. It is orthogonal and determined either from the covariance matrix or the correlation matrix of the input LRMIs. PCA performed using the covariance matrix is referred to as unstandardized PCA, while PCA performed using the correlation matrix is referred to as standardized PCA.

$$\begin{bmatrix} \mathrm{PC1} \\ \mathrm{PC2} \\ \cdots \\ \mathrm{PC}n \end{bmatrix} = \begin{bmatrix} v11 & v21 & \cdots & vn1 \\ v12 & v22 & \cdots & vn2 \\ \cdots & \cdots & \cdots & \cdots \\ v1n & v2n & \cdots & vnn \end{bmatrix} \begin{bmatrix} \mathrm{DN}^{l}_{\mathrm{MS1}} \\ \mathrm{DN}^{l}_{\mathrm{MS2}} \\ \cdots \\ \mathrm{DN}^{l}_{\mathrm{MSn}} \end{bmatrix}$$ -(3)

Where the transformation matrix

$$v = \begin{bmatrix} v11 & v12 & \cdots & v1n \\ v21 & v22 & \cdots & v2n \\ \cdots & \cdots & \cdots & \cdots \\ vn1 & vn2 & \cdots & vnn \end{bmatrix}.$$

$$\begin{bmatrix} \mathrm{DN}_{\mathrm{MS1}}^{h} \\ \mathrm{DN}_{\mathrm{MS2}}^{h} \\ \cdots \\ \mathrm{DN}_{\mathrm{MSn}}^{h} \end{bmatrix} = \begin{bmatrix} v11 & v12 & \cdots & v1n \\ v21 & v22 & \cdots & v2n \\ \cdots & \cdots & \cdots & \cdots \\ vn1 & vn2 & \cdots & vnn \end{bmatrix} \begin{bmatrix} \mathrm{DN}_{\mathrm{PAN}}^{h'} \\ \mathrm{PC2} \\ \cdots \\ PCn \end{bmatrix}.$$

-(4)

Similar to the IHS method, (3) and (4) can be merged as follows:

$$\begin{bmatrix} \mathrm{DN}_{\mathrm{MS1}}^{h} \\ \mathrm{DN}_{\mathrm{MS2}}^{h} \\ \cdots \\ \mathrm{DN}_{\mathrm{MSn}}^{h} \end{bmatrix} = \begin{bmatrix} \mathrm{DN}_{\mathrm{MS1}}^{l} \\ \mathrm{DN}_{\mathrm{MS2}}^{l} \\ \cdots \\ \mathrm{DN}_{\mathrm{MSn}}^{l} \end{bmatrix} + (\mathrm{DN}_{\mathrm{PAN}}^{h'} - \mathrm{DN}_{\mathrm{PAN}}^{l}) \begin{bmatrix} v11 \\ v21 \\ \cdots \\ vn1 \end{bmatrix}$$

-(5)

Where both are stretched to have same mean and variance as PC1.

C. High Pass Filtering Technique

The principle of HPF is to add the high-frequency information from the HRPI to the LRMIs to get the HRMIs [6]–[8]. The high-frequency information is computed by filtering the HRPI with a high-pass filter or taking the original HRPI and subtracting the LRPI, which is the low-pass filtered HRPI. This method preserves a high percentage of the spectral characteristics, since the spatial information is associated with the high-frequency information of the HRMIs, which is from the HRPI, and the spectral information is associated with the low-frequency information of the HRMIs, which is from the LRMIs. The mathematical model is

$$\mathrm{DN}_{\mathrm{MS}}^{h} = \mathrm{DN}_{\mathrm{MS}}^{l} + \left(\mathrm{DN}_{\mathrm{PAN}}^{h} - \mathrm{DN}_{\mathrm{PAN}}^{l}\right)$$

-(6)

Where $\mathrm{DN}_{\mathrm{PAN}}^{l} = \mathrm{DN}_{\mathrm{PAN}*}^{h} h_0$ and h_0 is a low-pass filter such as a boxcar filter. When boxcar filters are used, the filter length is crucial and must match the resolution ratio of the HRPI and LRMIs. A 3*3 boxcar filter is suitable for 1:2 fusion only, since the frequency response should have -dB cutoff (halved amplitude) at, where is the spatial frequency normalized to the sampling frequency. For 1:4 fusion, a 5*5 boxcar filter with cutoff frequency at roughly 0.125 must be used. Fig. 2 illustrates the frequency responses of 3*3, 5*5, and 7*7 boxcar filters. It shows that a smooth transition band is accompanied by a large ripple outside the pass-band [8].

D. Wavelet Transform Approach

The WT is suitable for image fusion, not only because it enables one to fuse image features separately at different scales, but also because it produces large coefficients near edges in the transformed image and reveals relevant spatial information [9]. The WT decomposes the signal based on elementary functions: the wavelets. Wavelets can be described in terms of two groups of functions: wavelet functions and scaling functions. It is also common to be defined the wavelet function as the "mother wavelet", and the scaling function is the "father" wavelet. So the transformations of the parent wavelets are "daughter" and "son" wavelets. In one-dimensional case, the continuous wavelet transform of a distribution *f* (t) can be expressed as

$$WT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\psi\left(\frac{t-b}{a}\right)dt \qquad \text{-(7)}$$

Where WT (a, b) is the wavelet coefficient of the function *f* (t) ; ψ the analyzing wavelet and a (a > 0) and b are scaling and translational parameters, respectively. Each base function is a scaled and translated version of a function $\psi(t)$ called Mother Wavelet.

To construct the sequence, the a' trous algorithm performs successive convolutions with a filter is used *h*o obtained from the scaling function. There are several possible ways of using the à trous algorithm in image fusion. Here, for the sake of clarity, we follow the additive method (AWRGB) described in [7]. The ATW method is given by

$$\mathrm{DN}^{h}_{\mathrm{MS}} = \mathrm{DN}^{l}_{\mathrm{MS}} + \left(\mathrm{DN}^{h}_{\mathrm{PAN}} - \mathrm{DN}^{l}_{\mathrm{PAN}}\right) \qquad \text{-(8)}$$

Where $\mathrm{DN}^{l}_{\mathrm{PAN}} = p_r, p_r$ is the approximation of the panchromatic image at decomposition level *r*, defined according to the resolution ratio. For 1 : 2 fusion, is set to 1; for 1 : 4 fusion, *r* is set to 2; and so on.

IV. COMPARISON AND ANALYSIS

The first two methods, i.e. PCA and IHS, are the most widely used for fusing remote sensing image data with different spatial resolutions. These methods are found in most of the commercial software in this field. They are simple to use but they present two important limitations. First, the high resolution image cannot be fused with one low spatial resolution image only but rather with three low spatial resolution images in the case of the IHS method and with three or more images for the PCA method. Second, these two methods are highly criticized because of the distortion of the spectral characteristics entailed between the fused images and the original low resolution images. Consequently, the resulting image does not preserve faithfully the colors found in the original images [8] [9] [10] [11].

The HPF method can be used to combine two images with different resolutions but the result is sensitive to the filtering used (filtering type, filter window size, etc.) and the mathematical operation used. It is this difficult to adopt a standard procedure for all users and the results depend highly on each application.

The WT approach is very often reported in the literature. The entire procedure is based on a complex and sophisticated pyramidal transformation where the result also depends on the level of decomposition and the filtering technique used to construct the wavelet coefficients.

Consequently, the two methods, i.e. HPF and WT are still in the development stage and do not find unanimity in the scientific community. They depend on numerous factors, which we do not master well. This is probably the reason why they are not part of the regular operations of most of the commercial software.

V. CONCLUSION

In this paper, we have presented the detailed information regarding four techniques (PCA, HIS, HPF, WT) used in image fusion. By using the comparisons between all the four techniques, we can draw the following conclusions: First, HPF transform the distortion of spectral characteristics and the IHS than wavelet transform method are small, with better spatial resolution; Second, after the image fusion wavelet transform not only the resolution is greatly improved, and the brightness and color in the image is also significantly enhanced. In the fused image, we have been able to easily carry out surface features of information extraction and image interpretation work; Third, HPF-based transformation method has better spatial resolution, increased clarity in the details, to better preserving the image of the spectral characteristic.

Every technique should take into account not the fusion purpose and the characteristics of individual sensors, but also particular image conditions, image geometry, noise corruption, required accuracy, and application-dependent data properties. In all above methods, no one has used edge preservation. So we need a method that also preserves image details during fusion.

REFERENCES

1. J. Flusser, F. Sroubek, B. Zitov, "Image Fusion: Principles, Methods, and Applications, Tutorial EUSIPCO 2007," Institute of Information Theory and Automation Academy of Sciences of the Czech Republic, 182 08 P.
2. Qian Lexiang. Remote sensing digital image processing and feature extraction Geo [M]. Beijing. Science Press, 2004.

3. Leica Geosystems.ERDAS Spatial Modeler Language Reference Manual [Z]. Atlanta. Georgia, 2003.
4. Rafael C. Gonzalez, Richard E. Woods. Digital Image Processing [M].USA. Addison-Wesley ,2001,26-35.
5. Tao Lixin, Wang Yu. IHS transform and wavelet transform of the remote sensing image fusion [J]. Surveying and Mapping Science and Engineering, 2005,(3):9-13.
6. R. A. Schowengerdt, Remote Sensing: Models and Methods for Image Processing, 2nd ed. Orlando, FL: Academic, 1997.
7. S. de Béthune, 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*, Jan. 28–30, 1998.
8. B. Aiazzi, L. Alparone, S. Baronti, and A. Garzelli, "Context-driven fusion of high spatial and spectral resolution images based on oversampled multi-resolution analysis," *IEEE Trans. Geosci. Remote Sens.*, vol. 40, no. 10, pp. 2300–2312, Oct. 2002.
9. J. Núñez, X. Otazu, O. Fors, A. Prades, V. Palà, and R. Arbiol, "Multiresolution-based image fusion with additive wavelet decomposition," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 3, pp. 1204–1211, May 1999.
10. Pellemans, A., Jordans, R., Allewijn, R., 1993. Merging multispectral and panchromatic SPOT images with respect to the radiometric properties of the sensor. *Photogrammetric Engineering & Remote Sensing*. Vol. 59, No. 1, pp. 81-87.
11. Zhang, Y. 1999. Anew merging method and its spectral and spatial effects. *International Journal of remote Sensing*. Vol. 20, pp.2003-2014.