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# Lunar Image Fusion using Wavelet Transform

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# Lunar Image Fusion using Wavelet Transform

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***Abstract* — This paper is an attempt to combine high resolution panchromatic lunar image with low resolution multispectral lunar image to produce a composite image using wavelet approach. There are many sensors that provide us image data about the lunar surface. The spatial resolution and spectral resolution is unique for each sensor, thereby resulting in limitation in extraction of information about the lunar surface. The high resolution panchromatic lunar image has high spatial resolution but low spectral resolution; the low resolution multispectral image has low spatial resolution but high spectral resolution. Extracting features such as craters, crater morphology, rilles and regolith surfaces with a low spatial resolution in multispectral image may not yield satisfactory results. A sensor which has high spatial resolution can provide better information when fused with the high spectral resolution. These fused image results pertain to enhanced crater mapping and mineral mapping in lunar surface. Since fusion using wavelet preserve spectral content needed for mineral mapping, image fusion has been done using wavelet approach.***

***Keywords-component; Multi sensor images, Lunar Images, Image fusion, Wavelet Transform, Fusion rule***

## I. INTRODUCTION

The Moon is Earth's only natural satellite. It is a good research subject. There are many satellites have been sent to explore the lunar surface. These satellites have taken different images of lunar surface for terrain and mineral mapping. There is high resolution panchromatic images of lunar surface which provides spatial information like crater, crater morphology, rilles and regolith surface and low resolution spectral image consisting of many bands provide information about the mineral abundance in the lunar surface but it fails to give spatial information. Hence combining high resolution panchromatic image with the high spectral resolution image provides a quality image with more information [2].

Lunar image fusion is the process of merging two or more lunar images to produce a single lunar image. This fused image should have more complete information of lunar surface which is more useful to extract more information.

The lower spatial resolution multispectral image needs to be fused with higher resolution panchromatic images to form a high resolution multispectral image [6]. Fusion preserves the spectral information content of the multispectral image and introduces the spatial information content of the panchromatic image in the fused image without introducing artifacts or inconsistencies, which may damage the quality of the fused image [7]. A well fused image by an effective fusion technique is useful not only for increasing the interpretability of human observers but also for improving the accuracy of the classification. In this paper, multispectral image fusion process using wavelet transform approach is performed. The image fusion is performed in two categories: image collected by the same sensors at the same time, and image collected by different sensors.

This paper is organized as section 2.Related Works. 3. Wavelet transforms 4.Image fusion.

## II. RELATED WORKS

Many image fusion algorithms have been developed [2]. The well known techniques are IHS (Intensity, Hue, and Saturation), PCA (Principal Component Analysis) and wavelet based fusion.

[4] Present the results of fusion of MODIS 8-day composite images in 7 bands (500m) and Landsat TM Mosaic images using bands 2, 4 and 7 for vegetation cover mapping of Krishna basin in south India. These images are resampled to 100 m resolution and fused using the IHS based fusion, which is applicable to only three bands, the SWIR, NIR and Green bands of the Landsat TM mosaic and of MODIS composite are made use of. It is observed that the PCA technique presents higher detail compared to the IHS technique and is applicable to all the seven bands. . An unsupervised classification of fused image obtained using PCA is carried out and the irrigated area is quantified. There is clearly an increase in the classification accuracy compared to the MODIS image. However, it is also seen that the Landsat classified image produces better result than

the PCA technique. Various researchers have attempted wavelet based image fusion in a variety of ways. Wavelet based image fusion of SAR and Landsat data for tropical land cover mapping is demonstrated by [3]. A Daubechies filter size of four has been used. The study area is the Lope Reserve in Gabon, Central Africa. On unsupervised classification based on ISOCLUS, it is observed that the fused image shows more localized details differentiating the different types of savannas and also mountain forest from mixed forest. It is opined that a statistical correlation of the original data with the fused data would have supported the study.

[4] Put forth two methods of wavelet based image fusion for wetland mapping. ENVISAT/Advanced Synthetic Aperture Radar (ASAR) Wide Swath data and SPOT VEGETZTION (VGT) D-10 data of Logone floodplain located in the Lake Chad Basin are fused. Method A is the normal wavelet based transform involving replacement of the approximation image of the ASAR image by a resampled VGT band. In method B, the two images are multiplied. The authors demonstrate that the latter method effectively reduces the incidence of artifacts due to the multiplication operation. The fused images are then classified and seven land use categories are differentiated including open water, three wetland types and three dry land types. Kappa statistics are the highest for the wavelet based fused images and correspond closely to the original images. This demonstrates that the wavelet transform reconstructs back an image of greater information content.

## III. WAVELET TRANSFORM

In this paper 2-D Discrete Wavelet Transform (DWT) is used for image fusion process. Wavelet transform is defined as sum over all time of the signal multiplied by scaled, shifted version of the mother wavelet $\Psi(t)$; wavelet transform decomposes a signal into the scaled and/or shifted versions of the mother wavelet

In DWT, instead of calculating wavelet coefficients at every possible scale, the scales and shifts are usually based on power of two. If we have a mother wavelet,

$$\Psi_{m,n}(t) = 2^{-m/2}\Psi\left(2^{-m}t - n\right) \tag{1}$$

A signal $f(t)$ can be expressed by wavelets as

$$f(t) = \sum_{m,n} c_{m,n}\Psi_{m,n}(t) \tag{2}$$

Where $m$ and $n$ are integers [5]. Here, $\Psi_{m,n}(t)$ is the dilated and/or translated version of the mother wavelet $\Psi$ . To implement an iterative wavelet transform $a_{m.n}$ coefficients are needed. These coefficients denote the approximation of $f$ at each scale. For example $a_{m,n}$ and $a_{m-1,n}$ designate the approximations at the resolution of $2^m$ and the coarser resolution $2^{m-1}$. $c_{m,n}$ also denotes the difference between one approximation and the other. To calculate $a_{m,n}$ and $c_{m,n}$ coefficients, a scaling function is necessary. Then, the convolution of scaling function and the signal is implemented at every scale using a low pass filter $h_n$ to calculate $a_{m,n}$ coefficients [5]. This process can be designated with the following equation.

$$a_{m.n} = \sum_k h_{2n-k}\, a_{m-1,k} \tag{3}$$

Similarly, by using a related high pass filter $g_n$ the $c_{m,n}$ coefficients are calculated using the following equation.

$$c_{m.n} = \sum_k g_{2n-k}\, a_{m-1,k} \tag{4}$$

For 2-D DWT, it is just necessary to separately filter and down sample the image in the horizontal and vertical directions. By doing this, the spatial resolution is halved at each level by subsampling the image by a factor two. Each image provides four sub-images at each resolution level corresponding to one approximation image (low spatial resolution) and three detail (horizontal, vertical and diagonal) images [8]. The same input image can be obtained by inverse DWT using calculated wavelet coefficients.

## IV. IMAGE FUSION

In image fusion, the first step is to prepare the input images for the fusion process. This includes registration and resampling of the input images [9]. Registration is to align corresponding pixels in the input images. This is usually done by geo-referencing the images to a map projection. Image registration can be performed with or without ground control points. The most accurate way is to rectify the images using ground control points. However in most cases, it is not possible to find ground control points in the input images. In such situations, taking the panchromatic image, which has better spatial resolution, is taken as reference image and registering the multispectral image with respect to panchromatic image can be good solution.

In the wavelet based fusion approach, the wavelet transform is applied on each registered source image to create a fused image that retain the most important features pertaining to all source images [11]. The fused image will then be exploited for human visual perception, object detection, and target recognition.

The wavelet transform is first used to decompose the panchromatic image to determine its wavelet coefficients and approximations. It is performed by cascading discrete convolutions of the source image with conjugate mirror filters H and G designed by Daubechies and subsampling of the output [6]. This yields four images in coarser resolution than the original image. The same operation is repeated for the multispectral image to determine its wavelet coefficients and approximations. Then a fusion decision map is generated based on a set of fusion rules which may be pixel or window based fusion rules.

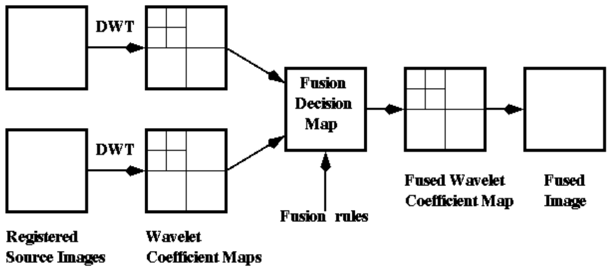



Figure1. Steps of Image fusion using Wavelet Transform

The fusion rule applied on approximation and detailed coefficients to obtain the better coefficients for constructing the fused image. The wavelet transform coefficients obtained from the input images need to be combined to form a new set of coefficients [6]. There are various fusion rules to form the fused wavelet coefficients matrix using the coefficients of the input images.

Different fusion rules have been implemented to the low sub bands and the detailed sub bands. The low frequency component of the fused image is replaced with the MVA multi-spectral coefficients. The detailed coefficient of the fused image is determined by the average gradient of the sub band. The gradient of an image f(x,y) at location(x,y) is the vector. The gradient has two important properties such as the gradient vector points to the direction of maximum rate of change of f(x,y) at the point (x,y) and magnitude of the gradient vector is

$$G[f(x,y)] = [(\partial f/\partial x) + (\partial f/\partial y)]^{1/2} \quad (5)$$

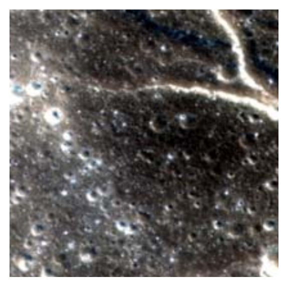
The average gradient of the detailed coefficients are computed and the coefficient having the largest value is selected and it is placed in the composite transform while the coefficient is less average gradient is discarded. The selection mode is implemented as:

CF(i,j) =CA(i,j), if GA(i,j)>GB(i,j) (6)
CF(i,j) =CB(i,j), if GB(i,j)>GA(i,j) (7)

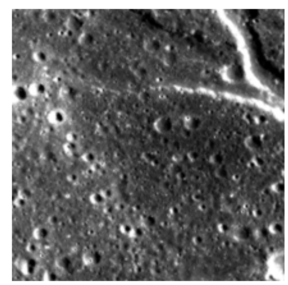
Where the symbols CA (i,j) and CB(i,j) denote the wavelet transform coefficients of the source image A and B respectively and the symbol CF(i,j) denote the wavelet transform coefficient of the fused image. After applying the fused rules the new fused wavelet coefficients are obtained and an inverse wavelet transform is performed. A high spatial resolution multispectral lunar image is obtained [10], having high spatial resolution of panchromatic image and also preserving the spectral information of multispectral image. The quality of the fused images has to be compared with the source images using measures such as visual comparison and image clarity. The performance of the image fusion techniques is evaluated by means of various measures such as Correlation Coefficient.

## V. Experiment and Results

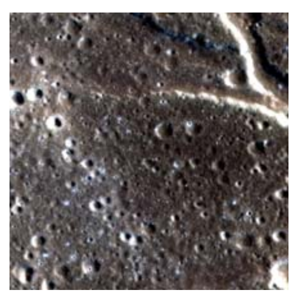
The above assessment technique is tested on fusion of TC panchromatic image of resolution 10m/pixel and the MVA multispectral image of resolution 20m/pixel, acquired over the same geographic location of moon. The MVA multi-spectral image is geometrically co-registered to the TC panchromatic image. The MVA images were also up-sampled to the same pixel size as TC PAN Image. The GS, PCA, and the Wavelet methods are employed to fuse TC PAN and MVA multi-spectral images. The color composite image of MVA 4, 2, 1 is shown in Figure 2a and figure 2b for the TC panchromatic image. Figure 2c, 2d, and 2e show the merged results of the MVA multi-spectral and TC panchromatic images by the PCA, GS and Wavelet methods, respectively. It can clearly be seen that the above fusion methods are capable of improving the spatial resolution with respect to the original MVA image.



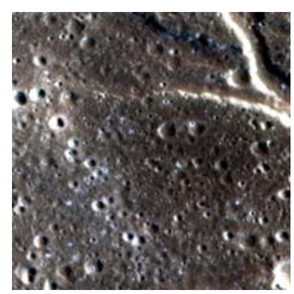
a. MVA



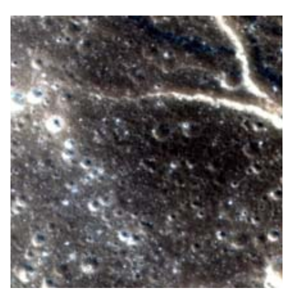
b. TC PAN image



c. PCA Fusion



d. GS Fusion



e. Wavelet Fusion

Figure2. The merged results of TC PAN and MVA images by PCA, GS and Wavelet Fusion methods

To quantify the behavior of the GS, PCA, and Wavelet methods we compute the correlation coefficient among the original MVA multispectral image as well as fused images. Table 1 presents the correlation coefficient of original MVA multispectral images and the fused images by GS, PCA and Wavelet approaches.

It is shown from Table 1 that from above fusion methods Wavelet has the larger correlation coefficient. This means that the spectral content of the fused images based on the above fusing methods can not completely reach the spectral content of the MVA multispectral image. It is obvious that the fusion methods are capable of improving the spatial resolution of the MVA multi-spectral images.

TABLE 1: CORRELATION COEFFICEIENT BETWEEN MVA(MS) AND FUSED IMAGE

| Fusion | Band 1 | Band 2 | Band 3 | Band 4 | Band 5 |
|---|---|---|---|---|---|
| PCA | 0.8780 33 | 0.8766 08 | 0.8790 3 | 0.8782 68 | 0.8795 64 |
| GS | 0.8782 91 | 0.8769 14 | 0.8790 52 | 0.8782 39 | 0.8793 37 |
| Wavel et | **0.9603 43** | **0.9829 01** | **0.9660 41** | **0.9572 78** | **0.9513 24** |

Therefore, multi-sensor image fusion is usually a trade-off between the spectral information from high spectral resolution sensor and the spatial structure from high spatial resolution sensor. Among these GS, PCA and Wavelet fusion methods, the Wavelet fusion method retains the most of the spectral and spatial information.

## VI. CONCLUSION AND FUTURE WORK

Since the image fusion is attempted using wavelet transform the distortion of information in fused image will be overcome. Wavelet transform has the advantage of retaining spectral information. The different approaches of wavelet based techniques such as discrete wavelet based fusion, Multi-wavelet based image fusion. Lifting wavelet and Dual tree wavelet fusion approaches will be attempted using the different wavelet techniques on lunar image and better information will be extracted and the results will be validated.

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