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Spectral Resolution Enhancement Using Optimum Wavelet Filter for Multi Spectral Image

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ABSTRACT

Spectral imaging sensors collect information in the form of reflectance spectrum in hundreds of contiguous narrow bands simultaneously. Hence, they are widely used in the range of military and civil applications. These applications require high spectral and spatial resolution data. Image Fusion is an important technique with many applications such as remote sensing, robotics and medical applications.

Multiple images has to be demultiplexed into each sub images based on the multiple spectrum and these sub images will be processed using wavelet filters based on high and low frequency sub-bands. The resultant images will be fused together to form a single image which is more suitable for human and machine perception.

Keywords: Multi spectral images, Hyper Spectral images, Stationary Wavelet Transform, Image Fusion.

1. INTRODUCTION

Image is the representation of object which exists in the real world in the form of 2d as well as 3d.Mostly images are captured with the help of optical device. Human eye which also captures Natural objects and phenomena. In some situations Images which are captured with the help of optical devices which will be useful for enhancing the image or extracting some information. This is called as image processing.

Image processing is closely related to computer graphics and computer vision. The images which are manually captured from the real world objects instead of being captured by optical devices such as camera. There are two types of image processing. They are analog and digital.

The process of combining relevant information from more than two images is called Image fusion; the fused image will have more sensitive data when comparing to the other images.

Image Fusion can be classified into spatial domain fusion and Transform domain fusion. The well-known image fusion methods are:

1) High pass filtering technique
2) IHS transform based image fusion
3) PCA based image fusion
4) Wavelet transforms image fusion
5) Pair-wise spatial frequency matching.

With the development of multi spectral (ms) and hyper spectral (HS) remote sensing images plays an important role in the fields of agriculture, medical and military. A popular fusion problem in remote sensing

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consists of merging a high spatial resolution hyper spectral (HS) image and a low spatial resolution multispectral (MS) image. To obtain images with good spectral and spatial resolutions the remote sensing community has been devoting increasing research efforts to the problem of fusing MS and MS images.

The fusion of HS and MS differs from pan sharpening images since both spatial and spectral information is contained in multi-bands. Therefore a lot of pan sharpening methods such as component substitution and relative spectral contribution are inefficient for the fusion of HS and MS images. The fusion of HS and MS images based on wavelet transform has also been explored. Fusing the multiple images into high and low frequency components was considered.

In this paper, we propose to evaluate the fused MS and HS images within a constrained optimization framework from the observed in the field of agricultural remote sensing images. The paper describes the theory of SWT (Stationary Wavelet Transform) by applying the fusion techniques of MS and HS images.

1.1. Limitations of Existing Techniques

Bicubic Interpolation Using Wavelet Coefficient on Image Fusion

Spectral Image Using Pan sharpened Image on Wavelet Filter Image Fusion

Pixel Level

Decision Level

Feature level

1.2. Issues to be Addressed

DWT is not a suitable transform for edge information

Contrast information loss due to averaging method

Maximizing approach is sensitive to sensor noise

Spatial distortion is high

More Computational complexity in the case of spectral level fusion.

2. RELATED WORK

Michael T.Eismann[6] et all proposed the MAP (maximum a posterior) method is obtained for enhancing the spatial and higher resolution of panchromatic and hyper spectral images. A SMM (stochastic mixing model) is used to develop the function of the images for reconstructing sub pixel level to estimate the images in a higher resolution .The MAP/SMM provides the better images with the higher resolution and reduces the noisy data.

YifanZhang [12] proposed the fusion technique in multispectral and hyper spectral images to enhance the spatial resolution. The enhancement is based on Bayesian estimation to describe both the images in an joint normal model. After the pan sharpening techniques is applied to the images, the results to be highly noise resistant and reliable in the fusion part.

Bo Huang [23] et al In this paper, proposed the spatial and spectral model that uses sparse matrix factorization to fuse the remote sensing images with different spatial and spectral data in two stages. By combining the spectral information with low and high spectral and spatial properties, the SASFM can generate the remote sensing data with HSaR and HSeR. In the first stage, the LSaR contains the pure signatures and in the second stage, the HSaR contains both high spectral and spatial data. The SASFM is tested with the stimulated data and landsat 7 Enhanced Thematic Mapper Plus and Terra Modulate

Resolution Imaging Spectroradiometre(MODIS). Finally the fusion process occurs with the help of MODIS and landsat.

Yee leung [24] et al proposed the adaptive intensity-hue-saturation (AIHS) method for pan sharpening image. From this method, the spatial details are injected into multi spectral image determined by a weighting matrix which based on the edges of panchromatic and MS images and MS bands. These are carried out under the experiments of IKONOS and Quick bird satellite images to show the spectral quality of AIHS and additive wavelet proportional methods. By formulating the IAIHS method the distortion problem can be overcome and it is more effective in the quality of spectral.

Zhao Chen [25] et al proposed the fusion technique in hyper spectral image and multi spectral image with the high and low spatial resolution. By applying the low spatial resolution hyper spectral images (HSIs) and high spatial resolution multispectral images (MSIs) are collected by the set of coupled sensors. It can be performed by the pan sharpening algorithms to divide the spectrum of HSIs into several regions and fusing HSIs and MSIs. RIBSR (ratio image –based spectral resampling) is used to interpolate the missing data to cover the multispectral band. Therefore the results can outperform the MAP or WT fusion methods by acquiring the high spatial resolution HIS with minimized distortions will be acquired.

Rakesh C Patel [26] et al In this paper DWT (discrete Wavelet Transform) is proposed for the filter coefficients using hyper spectral images for obtaining the high frequency wavelet. The algorithm is based on super resolution using the estimated wavelet filter coefficients (EWFCS).It improves the result of the spatial information of the data.

3. PROPOSED MODEL

Multi Spectral Image and hyper spectral Image Using combination of Wavelet Filter Coefficient and stationary wavelet transform based Image Fusion. Firstly the image is decomposed into high-frequency images and

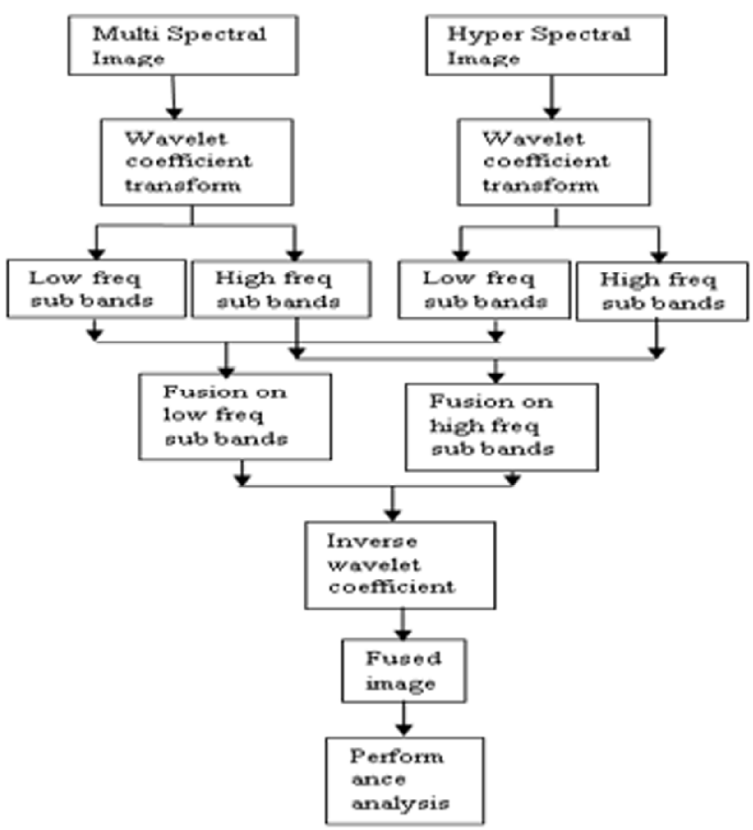

Figure 1: Architecture Diagram of Multi and Hyper Spectral Image

low frequency images with wavelet transform. Then the spatial frequency and the contrast of the low-frequency image are measured to determine the fused low frequency image. To the high-frequency image, we select the high- frequency coefficient based on the absolute value maximum principal and verify the consistency of these coefficients.

3.1. Advantages

It helps to describe complex scene in a single image.

Minimization of edge details loss due to no down sampling.

Less computational complexity and better visual perception.

High Performance Accuracy.

The edges of fused image preserved effectively after reconstruction.

It gives better contrast information.

4. STATIONARY WAVELET TRANSFORM

Wavelet Transform is a type of signal representation that gives the frequency content of the signal at a particular time or spatial location. A stationary Wavelet Transform (SWT) is a wavelet transform for which the wavelets are discretely sampled and decomposes the image into different sub band images. It splits component into numerous frequency bands called sub bands. They are LL, LH, HL, and HH sub bands. A high-frequency sub band contains the edge information of input image and LL sub band contains the clear information about the image.

Up sampling of coefficients will be performed in each row and column decomposition process to make lossless representation of edge details. The SWT of a signal *x* is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response.

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$$

The signal is also decomposed simultaneously using ahigh-pass filter*h*. The outputs give the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass).The outputs give the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). The filter outputs are thensub sampledby 2.

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n+1-k]$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled. Figure 4.1 shows the block diagram of filter analysis.

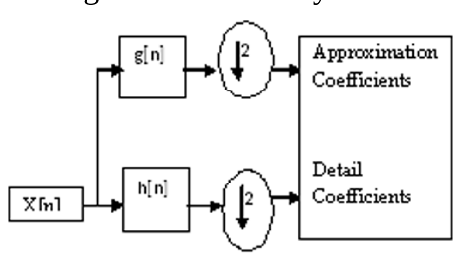

Figure 2: Block Diagram of Filter Analysis

With the sub sampling operator ↓

$$(y\ k)[n] = y[kn]$$

The above summation can be written more concisely.

$y = (x * g) \downarrow 2$

$y = (x * h) \downarrow 2$

However computing a complete convolution $x * g$ with subsequent down sampling would waste computation time. The Lifting scheme is an optimization where these two computations are interleaved.

5. STEPS OF STATIONARY WAVELET TRANSFORM (SWT)

STEP 1: The SWT of a signal x is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution of the two.

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$$

STEP 2: The signal is also decomposed simultaneously using a high-pass filter$h$. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass).

It is important that the two filters are related to each other and they are known as a quadrature mirror filter.

STEP 3: The filter outputs are then sub sampled by 2 general equations. Thus we obtain two values from the given equation (low, high).

STEP 4:

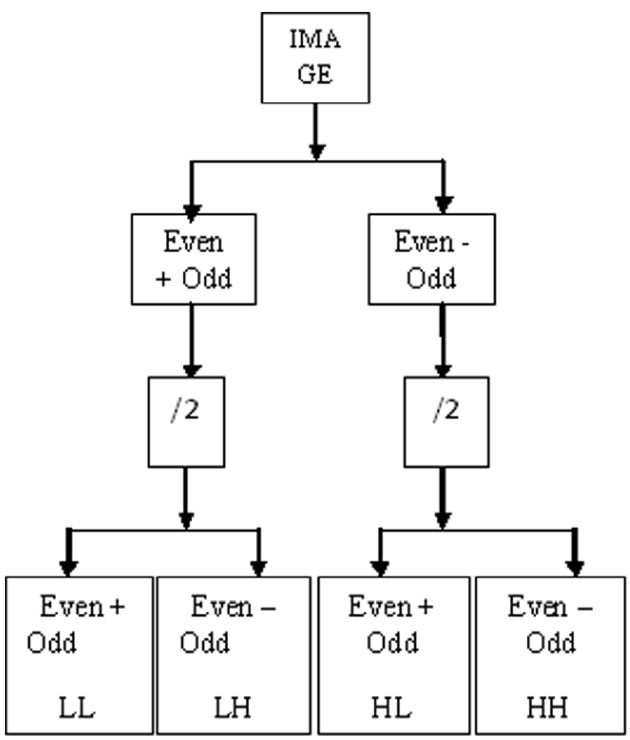

Figure 3: Filter Structure

From the two values, Y low and Y high we obtain two set of pixel value. From the pixel values obtained we can further divide it using the similar formula to obtain the final four values. The final four values as LL, LH, HL, HH. In fig 5.1 describes the filter Structure of the images by using down sampling techniques. In this filter Structure, the low and high pass filters will be displayed in four values to get the clear images for further fusion.

6. IMAGE FUSION

6.1. Fusion of Low-frequency Coefficients

Considering the approximate information is constructed by the low-frequency coefficients, average rule is adopted for low-frequency coefficients. Suppose $B_F\ (x, y)$ is the fused low-frequency coefficients, then

$$B_F(x, y) = \frac{B_1(x, y) + B_2(x, y)}{2}$$

where $B_1(x, y)$ and 2 $B_2\ (x, y\ )$ denote the low-frequency coefficients of source images.

6.2. Fusion of High-frequency Coefficients

High-frequency coefficients always contain edge and texture features. The maximum coefficients of detail components are respectively taken as the most salient features with the corresponding local window along horizontal, vertical, and diagonal directions.

$$D_v^j, F(i, j) = \begin{cases} Dvj, X(i, j), if Cvj, X(i, j) > Cvj, Y(i, j) \\ Dvj, Y(i, j), Otherwise \end{cases}$$

$$D_h^j, F(i, j) = \begin{cases} Dhj, F(i, j), if Chj, X(i, j) > Chj, Y(i, j) \\ Dhj, Y(i, j), Otherwise \end{cases}$$

6.3. Performance Evaluation of Fusion

It has been common to evaluate the result of fusion visually. According to visual evaluation, human judgment determines the quality of the image. Some independent and objective observers give grade to corresponding image and the final grade is obtained by taking the average or weighted mean of the individual grades. Obviously this evaluation method has some drawbacks, namely it is not accurate and depends on the observer's experience.

For an accurate and truthful assessment of the fusion product some quantitative measures (indicator) is required. Two different measures are used in this project to evaluate the results of fusion process. They are Information Entropy and Root Mean Square Error.

Peak –signal-to noise ratio and Mean square error:

How do we determine the quality of a digital image? Human eyes perception is the fastest approach. However, although this criterion is effective in general, the results may differ from person to person.

To establish an objective criterion for digital image quality, a parameter named PSNR (Peak Signal to Noise Ratio) is defined in equation as follows:

$$PSNR = 10*\log10\ (255*255/MSE)$$

Where MSE (Mean Square Error) stands for the mean-squared difference between the cover-image and the stego-image.

The mathematical definition for MSE is defined in equation as follows:

$$MSE = 1/(M*N) \sum_{i=1}^{M} \sum_{j=1}^{N} (a_{ij}-b_{ij})^2$$

In this above equation a_{ij} means the pixel value at position (i,j) in the input image and b_{ij} is the pixel value at the same position in the output image.

The calculated PSNR usually adopts dB value for quality judgement. The larger PSNR is, the higher the image quality is (which means there is only little difference between the input-image and the fused-image). On the contrary, a small dB value of PSNR means there is great distortion between the input-image and the fused-image.

Entropy:

It is useful to determine the significant information from the image based on the probability of pixel values

$$S = -\sum_{x}\sum_{y} p(x,y) \log p(x,y)$$

Where, p(x, y) is the probability of each gray level.

7. CONCLUSION

The SWT for remotely sensed MS and HS images with the aim of generating the clear data of MS and HS images. By using SWT, a spectral resolution of MS image with the spectral resolution of HS image can be generated in the form of RGB plane. The resultant images are generated by inverse SWT. Further it undergoes the performance evaluation of fusion methods to get the clear MS and HS images.

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