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Research Article

Wavelet Resolution Merge and Histogram Equalization Applied to Remotely Sensed Data

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Abstract

Classification of Low-Resolution Remotely Sensed data using suitable classification methods depends on the quality of the data. For low resolution images, it is always difficult if not impossible to differentiate classes as the number of classes is increased above 8. Hence, as a prerequisite to image classification, Pan Sharpening or merging the low resolution image with a high resolution image of the same area considered, can improve the quality of the data. The method used for Pansharpening in this paper is Wavelet Resolution Merge. Further, image enhancement techniques can be applied to data for making the considered dataset more interpretable. In this paper, Histogram equalization is employed on the data after Pansharpening process to study the improvements. Image parameters such as Standard Deviation and Mean are considered for decision making. It has been found that, by Pansharpening and Histogram Equalization, the quality of the input data is improved, which can further yield better classification results.

Keywords: *Pansharpening, Resolution Merge, Wavelet Transform, Histogram Equalization, Image Fusion, Remote Sensing*

1. Introduction

Pansharpening is a process of merging high-resolution panchromatic and lower resolution multispectral imagery to create a single high-resolution colour image. Google Maps and nearly every map creating company use this technique to increase image quality. Pansharpening produces a high-resolution colour image from three, four or more low-resolution multispectral satellite bands plus corresponding high-resolution panchromatic bands.

Pansharpening uses spatial information in the high-resolution gray scale band and colour information in the multispectral bands to create a high-resolution colour image, essentially increasing the resolution of the colour information in the data set to match that of the panchromatic band.

Common colour-space transformations used for pan sharpening are HSI (hue-saturation-intensity), and YC_bC_r. The same steps can also be performed using wavelet decomposition or PCA and replacing the first component with the pan band.

Pansharpening techniques can result in spectral distortions when pan sharpening satellite images as a result of the nature of the panchromatic band. The Landsat panchromatic band for example is not sensitive to blue light. As a result, the spectral characteristics of the raw pansharpened colour image may not exactly match those of the corresponding low-resolution RGB image, resulting in altered colour tones.

2. Prerequisites and Limitations

- *Precise Coregistration*

A first prerequisite is that the two images be precisely co-registered. For some sensors (e.g., Landsat 7 ETM+) this co-registration is inherent in the dataset. If this is not the case, a greatly over-defined 2nd order polynomial transform should be used to coregister one image to the other. By over-defining the transform (that is, by having far more than the minimum number of tie points), it is possible to reduce the random RMS error to the subpixel level. This is easily accomplished by using the Point Prediction option in the GCP Tool. In practice, well-distributed tie points are collected until the predicted point consistently falls exactly where it should. At that time, the transform must be correct. This may require 30-60 tie points for a typical Landsat TM—SPOT Pan Co-registration.

When doing the coregistration, it is generally preferable to register the lower resolution image to the higher resolution image, i.e., the high resolution image is used as the Reference Image. This will allow the greatest accuracy of registration. However, if the

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lowest resolution image has georeferencing that is to be retained, it may be desirable to use it as the Reference Image. A larger number of tie points and more attention to precise work would then be required to attain the same registration accuracy. Evaluation of the X- and Y-Residual and the RMS Error columns in the ERDAS IMAGINE GCP Tool will indicate the accuracy of registration.

It is preferable to store the high and low resolution images as separate image files rather than Layerstacking them into a single image file. In ERDAS IMAGINE, stacked image layers are resampled to a common pixel size. Since the Wavelet Resolution Merge algorithm does the pixel resampling at an optimal stage in the calculation, this avoids multiple resamplings.

After creating the coregistered images, they should be codisplayed in an ERDAS IMAGINE Viewer. Then the Fade, Flicker, and Swipe Tools can be used to visually evaluate the precision of the coregistration.

- *Identical Spectral Range*

Secondly, an underlying assumption of resolution merge algorithms is that the two images are spectrally identical. Thus, while a SPOT Panchromatic image can be used to sharpen TM bands 1-4, it would be questionable to use it for TM bands 5 and 7 and totally inappropriate for TM band 6 (thermal emission). If the datasets are not spectrally identical, the spectral fidelity of the MS dataset will be lost.

It has been noted that there can be spectrally-induced contrast reversals between visible and NIR bands at, for example, soil-vegetation boundaries. This can produce degraded edge definition or artifacts (Lemeshewsky G. P, 1999a, 2002b)

- *Temporal Considerations*

A trivial corollary is that the two images must have no temporally-induced differences. If a crop has been harvested, trees have dropped their foliage, lakes have grown or shrunk, etc., then merging of the two images in that area is inappropriate. If the areas of change are small, the merge can proceed and those areas removed from evaluation. If, however, the areas of change are large, the histogram matching step may introduce data distortions.

- *Theoretical Limitations*

As described in the discussion of the discrete wavelet transform, the algorithm downsamples the high spatial resolution input image by a factor of two with each iteration. This produces approximation (a) images with pixel sizes reduced by a factor of two with each iteration. The low (spatial) resolution image will substitute exactly for the “a” image only if the input images have relative pixel sizes differing by a multiple of 2. Any other pixel size ratio will require resampling of the low (spatial) resolution image prior to substitution. Certain ratios can result in a degradation of the substitution image that may not be fully overcome by the subsequent wavelet sharpening. This will result in a less than optimal enhancement. For the most common scenarios, Landsat ETM+, IKONOS and QuickBird, this is not a problem.

Although the mathematics of the algorithm is precise for any pixel size ratio, a resolution increase of greater than two or three becomes theoretically questionable. For example, all images are degraded due to atmospheric refraction and scattering of the returning signal. This is termed “point spread”. Thus, both images in a resolution merge operation have, to some (unknown) extent, been “smeared”. Thus, both images in a resolution merge operation have, to an unknown extent, already been degraded. It is not reasonable to assume that each multispectral pixel can be precisely devolved into nine or more subpixels.

3. Wavelet Resolution Merge

The ERDAS IMAGINE Wavelet Resolution Merge allows multispectral images of relatively low spatial resolution to be sharpened using a co-registered panchromatic image of relatively higher resolution. A primary intended target dataset is Landsat 7 ETM+. Increasing the spatial resolution of multispectral imagery in this fashion is, in fact, the rationale behind the Landsat 7 sensor design.

The ERDAS IMAGINE algorithm is a modification of the work of King and Wang with extensive input from Lemeshewsky. Aside from traditional Pan-Multispectral image sharpening, this algorithm can be used to merge any two images, for example, radar with SPOT Pan (Lemeshewsky G. P, 1999, 2002, King R. L *et al*, 2001)

Fusing information from several sensors into one composite image can take place on four levels; signal, pixel, feature, and symbolic. This algorithm works at the pixel level. The results of pixel-level fusion are primarily for presentation to a human observer/analyst (Rockinger O *et al*, 1998). However, in the case of pan/multispectral image sharpening, it must be considered that computer-based analysis (e.g., supervised classification) could be a logical follow-on. Thus, it is vital that the algorithm preserve the spectral fidelity of the input dataset.

- *Wavelet Theory*

Wavelet-based image reduction is similar to Fourier transform analysis. In the Fourier transform, long continuous (sine and cosine) waves are used as the basis. The wavelet transform uses short, discrete “wavelets” instead of a long wave. Thus the new transform is much more local (Szabo V *et al*, 1997). In image processing terms, the wavelet can be parameterized as a finite size moving window.

A key element of using wavelets is selection of the base waveform to be used; the “mother wavelet” or “basis”. The “basis” is the basic waveform to be used to represent the image. The input signal (image) is broken down into successively smaller multiples of this basis.

Wavelets are derived waveforms that have a lot of mathematically useful characteristics that make them preferable to simple sine or cosine functions. For example, wavelets are discrete; that is, they have a finite length as opposed to sine waves which are continuous and infinite in length. Once the basis waveform is mathematically defined, a family of multiples can be created with incrementally increasing frequency. For example, related wavelets of twice the frequency, three times the frequency, four times the frequency, etc. can be created.

Once the waveform family is defined, the image can be decomposed by applying coefficients to each of the waveforms. Given a sufficient number of waveforms in the family, all the detail in the image can be defined by coefficient multiples of the ever-finer waveforms.

In practice, the coefficients of the discrete high-pass filter are of more interest than the wavelets themselves. The wavelets are rarely even calculated (Shensa M.J, 1992). In image processing, we do not want to get deeply involved in mathematical waveform decomposition; we want relatively rapid processing kernels (moving windows). Thus, we use the above theory to derive moving window, high-pass kernels which approximate the waveform decomposition.

For image processing, orthogonal and biorthogonal transforms are of interest. With orthogonal transforms, the new axes are mutually perpendicular and the output signal has the same length as the input signal. The matrices are unitary and the transform is lossless. The same filters are used for analysis and reconstruction.

In general, biorthogonal (and symmetrical) wavelets are more appropriate than orthogonal wavelets for image processing applications (Szabo V *et al*, 1997). Biorthogonal wavelets are ideal for image processing applications because of their symmetry and perfect reconstruction properties. Each biorthogonal wavelet has a reconstruction order and a decomposition order associated with it. For example, biorthogonal 3.3 denotes a biorthogonal wavelet with reconstruction order 3 and decomposition order 3. For biorthogonal transforms, the lengths of and angles between the new axes may change. The new axes are not necessarily perpendicular. The analysis and reconstruction filters are not required to be the same. They are, however, mathematically constrained so that no information is lost, perfect reconstruction is possible and the matrices are invertible.

The signal processing properties of the Discrete Wavelet Transform (DWT) are strongly determined by the choice of high-pass (bandpass) filter (Shensa M.J, 1992). Although biorthogonal wavelets are phase linear, they are shift variant due to the decimation process, which saves only even-numbered averages and differences. This means that the resultant subimage changes if the starting point is shifted (translated) by one pixel. For the commonly used, fast discrete wavelet decomposition algorithm, a shift of the input image can produce large changes in the values of the wavelet decomposition coefficients. One way to overcome this is to use an average of each average and difference pair (Mallat S, 1998).

Once selected, the wavelets are applied to the input image recursively via a pyramid algorithm or filter bank. This is commonly implemented as a cascading series of highpass and lowpass filters, based on the mother wavelet, applied sequentially to the low-pass image of the previous recursion. After filtering at any level, the low-pass image (commonly termed the "approximation" image) is passed to the next finer filtering in the filter bank. The high-pass images (termed "horizontal", "vertical", and "diagonal") are retained for later image reconstruction. In practice, three or four recursions are sufficient.

- *Histogram Equalization*

Histogram modelling techniques (*e.g.* histogram equalization) provide a sophisticated method for modifying the dynamic range and contrast of an image by altering that image such that its intensity histogram has a desired shape. Unlike contrast stretching histogram modelling operators may employ *non-linear* and *non-monotonic* transfer functions to map between pixel intensity values in the input and output images. Histogram equalization employs a monotonic, non-linear mapping which re-assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities (*i.e.* a flat histogram). This technique is used in image comparison processes (because it is effective in detail enhancement) and in the correction of non-linear effects introduced by, say, a digitizer or display system. Histogram modelling is usually introduced using continuous, rather than discrete, process functions. Therefore, we suppose that the images of interest contain continuous intensity levels (in the interval [0,1]) and that the transformation function f which maps an input image A(x,y) onto an output image B(x,y) is continuous within this interval. Further, it will be assumed that the transfer law (which may also be written in terms of intensity density levels, *e.g.,* $D_B = f(D_A)$ is single-valued and monotonically increasing (as is the case in histogram equalization) so that it is possible to define the inverse law $D_A = f^{-1}(D_B)$. An example of such a transfer function is illustrated in Fig.1.

All pixels in the input image with densities in the region D_A to D_A+dD_A will have their pixel values re-assigned such that they assume an output pixel density value in the range from D_B to D_B+dD_B. The surface areas $h_A(D_A)dD_A$ and $h_B(D_B)dD_B$ will therefore be equal, yielding:

$$h_B(D_B) = h_A(D_B) \div dD_A \quad (1)$$

Where, $d(x) = \dfrac{df(x)}{dx}$

This result can be written in the language of probability theory if the histogram *h* is regarded as a continuous probability density function *p* describing the distribution of the (assumed random) intensity levels:

$$P_B(D_B) = P_A(D_A) \div d(D_A) \quad (2)$$

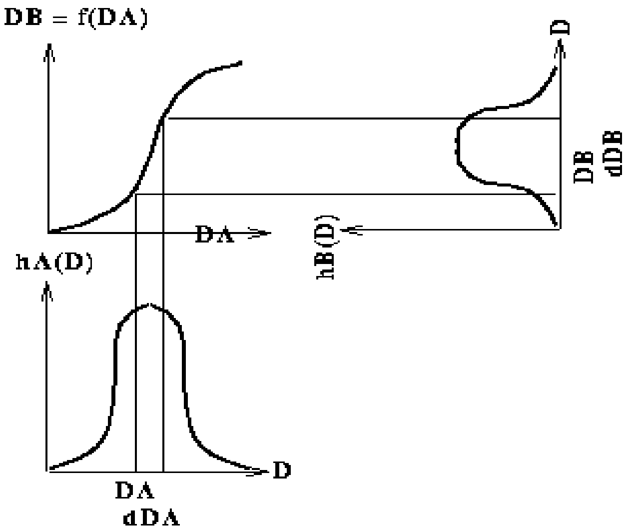

Fig. 1 Histogram transformation function

In the case of histogram equalization, the output probability densities should all be an equal fraction of the maximum number of intensity levels in the input image D_M (where the minimum level considered is 0). The transfer function (or point operator) necessary to achieve this result is simply:

$$d(D_A) = D_M * P_A(D_A) \quad (3)$$

Therefore,

$$f(D_M) = D_M \int_0^{D_A} p_A(u)du = D_M * F_A()D_A \quad (4)$$

where, F_A (D_A) is simply the cumulative probability distribution (i.e. cumulative histogram) of the original image. Thus, an image which is transformed using its cumulative histogram yields an output histogram which is flat!

A digital implementation of histogram equalization is usually performed by defining a transfer function of the form:

$$f(D_A) = \max(0, round[D_M * n_k / N^2] - 1) \quad (5)$$

Where *N* is the number of image pixels and n_k is the number of pixels at intensity level k or less.

In the digital implementation, the output image will not necessarily be fully equalized and there may be `holes' in the histogram (*i.e.* unused intensity levels). These effects are likely to decrease as the number of pixels and intensity quantization levels in the input image are increased.

4. Result and Analysis

To validate the applicability of the proposed fusion method, a case study is presented in this section, which is carried out on IRS-p6/LISS III sample image with 23.5 meter spatial resolution. The area considered is Mysore District, Karnataka, India, as illustrated in Fig.2. Fig.3 illustrates the panchromatic image of the same area with spatial resolution of 5 meter. The software used for performing Pansharpening and Histogram equalization is ERDAS IMAGINE v9.1

Fig.4 indicates the fused image after wavelet resolution merge technique is carried over images shown in Fig.2 and Fig.3. To improve the image characteristics, histogram equalization is carried out on pansharpened image and is presented in Fig.5.

Table I and Table II illustrate image parameters for the fused image before and after histogram equalization method is applied.

Table 1 Results for Pan Sharpening before histogram equalization is applied

Method Applied	Min	Max	Mean	Std dev
Wavelet Transform without Histogram Equalization image	0	254	37.754	48.577
Original Multispectral Image	0	255	38.158	49.491
Original Panchromatic Image	0	255	69.108	74.906

Table 2 Results for Pan Sharpening after histogram equalization is applied

Method applied	Min	Max	Mean	Std dev
Wavelet Transform After Histogram Equalization Image	77	255	127.471	65.168
Original Multispectral Image	0	255	38.158	49.491
Original Panchromatic Image	0	255	69.108	74.906

Fig.6 indicates a bar-chart indicating the changes in image parameters before and after histogram equalization technique being applied to fused image. Image parameters such as Maximum and Minimum Intensity value of the pixels, Average Intensity values of the pixels, and standard deviation are considered for result analysis. As it can be seen from Fig.6, the mean and standard deviation values undergo significant change once histogram equalization method is applied.

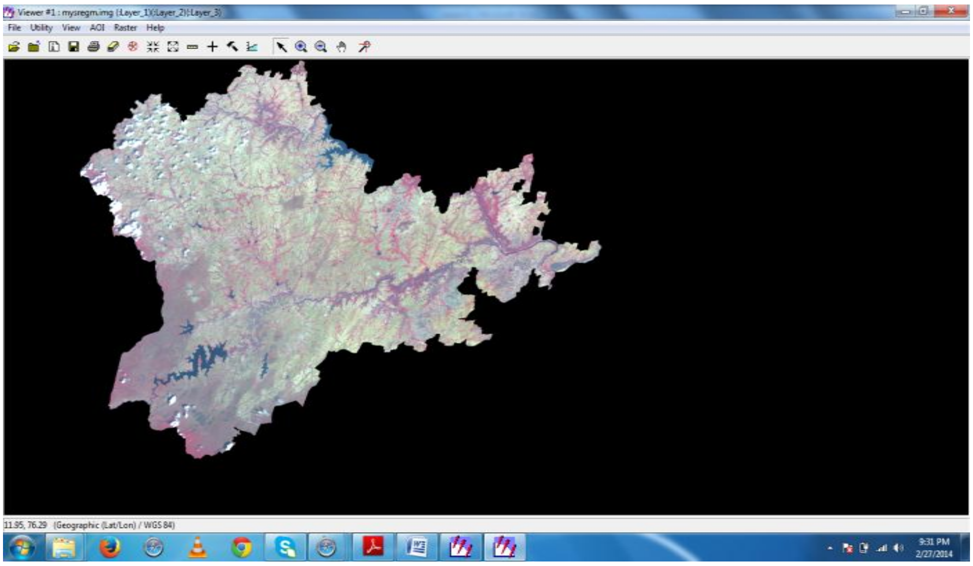

Fig.2 3.5 meter Spatial Resolution Multispectral Data Considered for case study

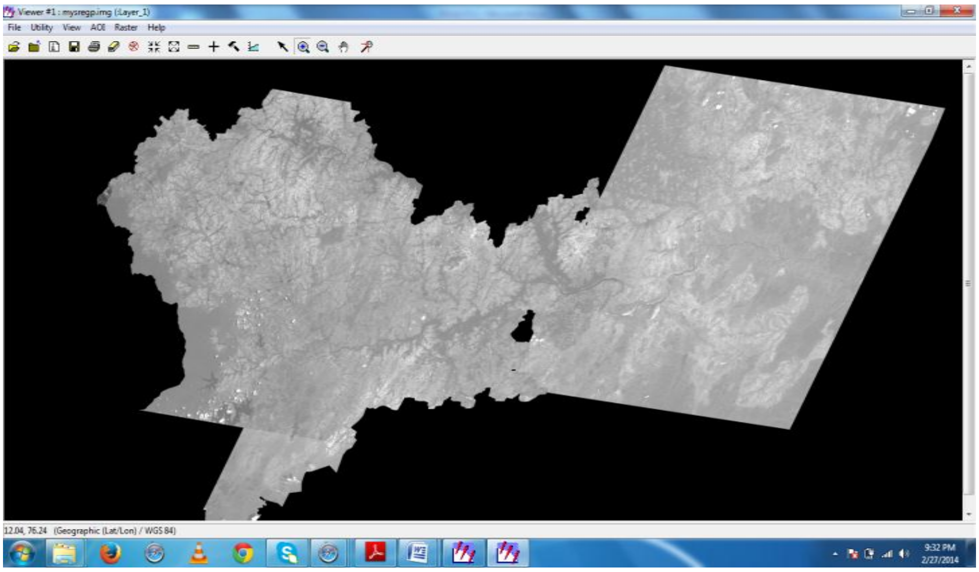

Fig.3 5 meter Panchromatic Data considered for case Study

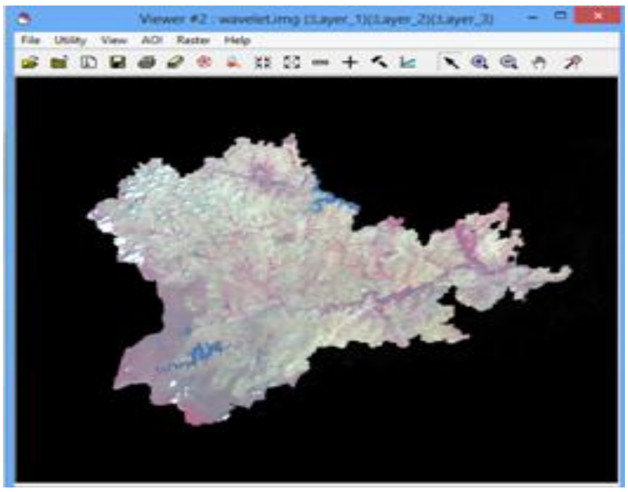

Fig.4 Wavelet resolution Merged Image

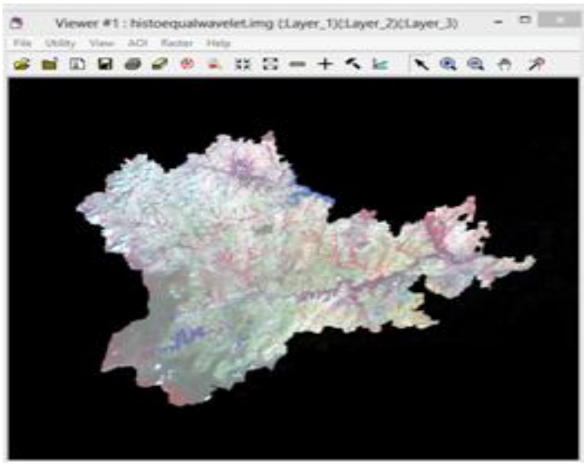

Fig. 5 Wavelet resolution Merged Image After Histogram Equalization Process

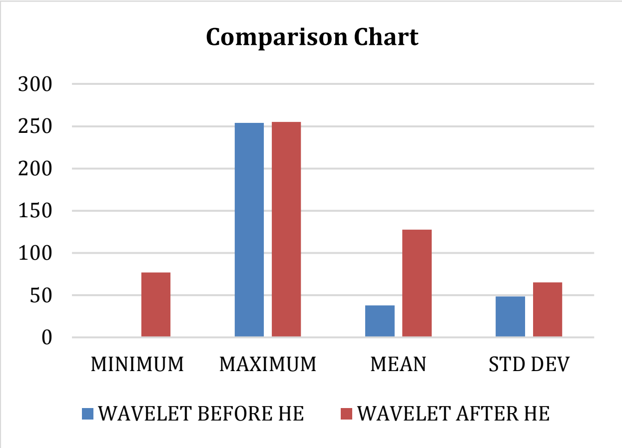

Fig. 6 Comparison Chart showing Variations in Image Parameters for Wavelet Transformation merged image before and after Histogram Equalization Process.

Conclusions

Pansharpening plays a vital role in the Remote Sensing Image classification results. It is learnt from the literature survey that Pansharpened images tend to yield higher classification accuracy because of increased spatial resolution process during merging process. It is also learnt from the literature survey that as the Spatial resolution of the image increases, the classification process becomes less complex leading to clear bifurcation of image classes.

In this paper, Wavelet resolution merge technique is used for fusing the data and the results are analyzed. The image parameters are listed in TABLE I to illustrate the changes in image parameters before and after Wavelet resolution merge technique is applied. The results show positive growth of image parameters. Histogram Equalization provides a sophisticated method for modifying the dynamic range and contrast of an image by altering that image such that its intensity histogram has a desired shape. TABLE II shows the results for the image after it has gone through Wavelet resolution merge and Histogram Equalization. There is clearly improvement is image quality. Hence, we conclude that both Resolution merge and histogram Equalization techniques improve the quality of the data for further processing. For more satisfactory results, image classification and accuracy assessment methods can be carried out.

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