COLOR SATELLITE IMAGES DENOISING USING WAVELETS

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ABSTRACT

The satellite image is multi band image,the first three bands have the largest wavelength and image information and usually contain noise due to different reason such as image band acquisition or transmission.

In this paper an adaptive method implemented to denoising the satellite image by using the Haar wavelet transform applied to the principle components bands of the satellite image.

The image denoising by Haar wavelet transform is applied on the first band(PC1).This band has found contain about 90% of the image information, in this case the time required for processing and storage size are reduced ,and the image appearance are more suitable than the processing the image bands directily.

الخلاصة

تعتبر صورة الأقمار الصناعيةَ صورة ُمتعددة الحزمِ، الحزم الثلاث الأولى لَها الطولُ الموجي الأكبرُوالجزء الاكبر من معلومات الصورة, هذه الحزم تحتوي نسبه عاليه من الضوضاء نتيجة لعمليه استحصال المعلومات او ارسلها.

في هذا البحث أستخدمت Haar wavelet لاستخلاص الضوضاء من حزم الصور الفضائية وتم مقارنة النتائج من خلال قياس نسبة الضوضاء ومقارنتها مع الطرق التقليديه.من خلال دراسة توزيع المعلومات وجد ان الحزمه الاولى تحتوي تقريبا على 90 % من معلومات الصورة ولهذا تم ستخدام Haar wavelet على هذه الحزمه فقط ,وبهذا تم تقليل الوقت المستغرق والمساحه الخزنيه المطلوبه في حالة معالجه الصور الفضائية.

KEYWORDS

satellite image,principle component,Wavelet transform

INTRODUCTION

Satellite images are multi band, i.e. the image is consisting from three bands or more according to satellite sensor used to capture these images. But usually only the first three bands used to represent these images as true color images with RGB bands, and contain noise due to image acquisition, transmission error or compression side effects. The noise causes great problems to image processing algorithims. Only when the image de-noising is effective the edge detection is proper. In other case the edge detection is significantly noised [Scoott E Umbaugh(1998)].

De-noising is typically handled by smoothed filters applied to the image three bands .But smoothing can delete useful information or distort the input image [Gomies(1997)].

The main steps of the proposed strategy are (1) transform the image to it s principle components bands ,(2) image denoising using wavelet transformation implemented on the first principal component only ,(3) extract back the new image band from it is principle components bands.

PRINCIPAL COMPONENTS TRANSFORM (PCT)

Some of the images processing techniques applied on two or all the bands of an image. If there are many bands, it becomes difficult to visualize as well as expensive to process all the bands. The principal components transform is based on statistical properties of the image,it can be applied to any n-dimensional mathematical space to collapse any multiband image down to fewer bands. In this paper, the PCT is applied to the three –dimensional color space.Each pixel in the (n)-spaced image may be considered as a point in (n) dimensional pixel space. The set of all pixels in the image becomes a distribution of points in this space.

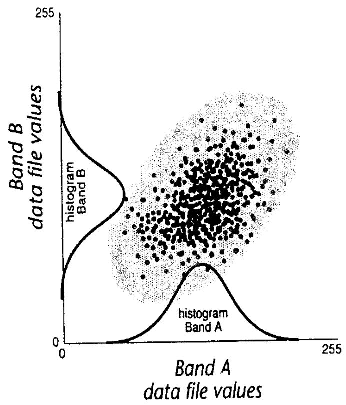
The effect of computing the principal components of a distribution is to determine a new set of axes with two related properties [R. Wilson 1988].

1- The axes may be ordered by their "information content", thus using only the first axis, the best one dimensional representation of the data is obtained, by using the first two, the best two dimensional representation, and so on.

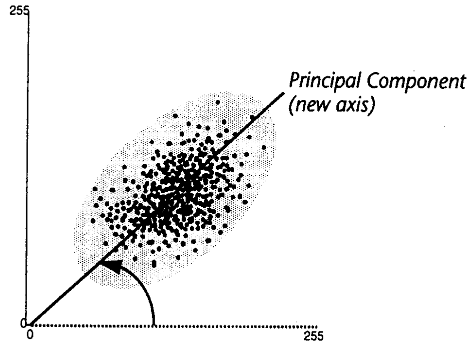
2- The data expressed in the new axes are uncorrected .

The PCT is easily explained graphically with an example of data in two bands. Figure (1-a) shows the relationships of data file values in two bands. The values of one band are plotted against those of the other. If both bands have normal distribution, an ellipse shape results, (for three band ellipsoid shape results).

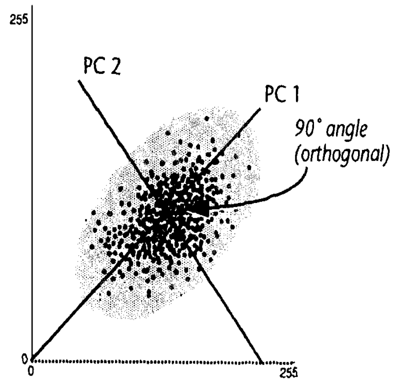
To perform principal component analysis, the axes of the spectral space are rotated, changing the coordinates of each pixel in spectral space, and the data file values as well. The new axes are parallel to the axes of the ellipse, major (longest) axis of the ellipse, is called the first principal component of the data, a new axis of the spectral space is defined by this first principal component as shown in Figure (1-b), and since in spectral space, the coordinates of the points are the data file values, new data file values are derived from this process. These values are stored in the first principal component band of a new data file. The second principal component is the widest transect of the ellipse that is orthogonal (perpendicular) to the first principal component as shown in Figure (1-c). The second principal component describes the largest amount of variance in the data that is not already described by the first principal component . The eignvectors and eignvalues represent the lengths and directories of the principal axes. [ERDAS Inc(1995)]. Figure (2) represent the implemented block diagram to explain the process of extract the pinciple bands from RGB (multiband) satellite image.



a



b



c

Figure (1-a, b ,c) Transformation of the two bands by PCT

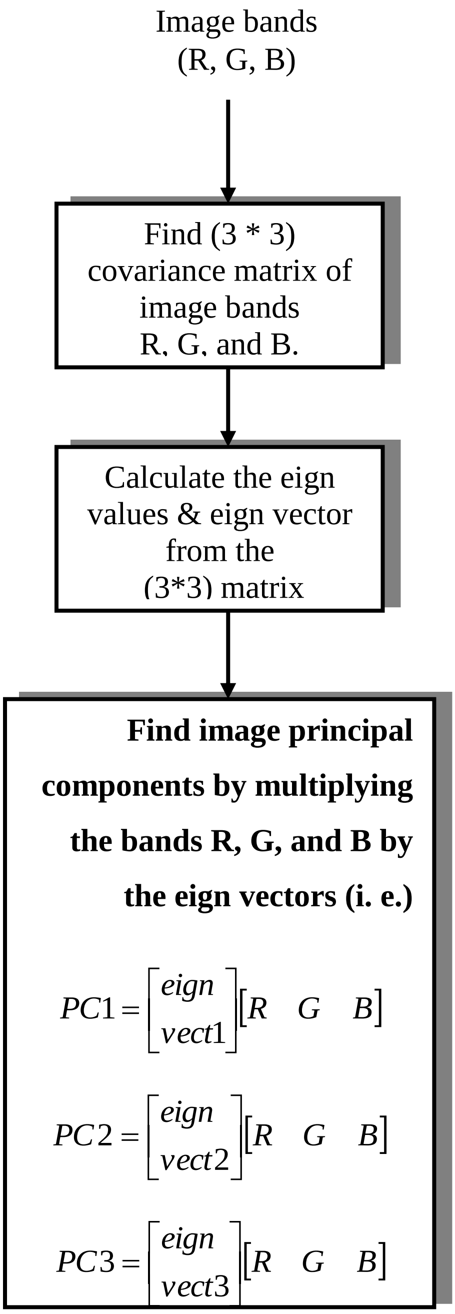


Figure (2) PCT block diagram

$$PC_j = \sum_{i}^{3} e_{ij} \; b_i$$

IMAGE DE-_NOISING USING WAVELET TRANSFORM

Wavelet transforms used to represent signals with a high degree of sparisty.This is the principle behind a non linear wavelet based signal estimation technique known as wavelet denoising. Aprecise explanation of the wavelet denoising procedure can be given as follows. Assume that the observed data is

X(t)= S(t)+N(t)

Where S(t) is the uncorrupted signal with addaitive noise N(t)[R.Gonzalez and P.Wintz(2001)]. Let W(.) and $\hat{w}$ denote the forwared and the inverse wavelet transformation operatators .Let D(.,λ) denote the denoising operator with threshold λ. This paper intend to denoise X(t) to recover $\hat{S}$ (t) as an estimate of S(t). The procedure can be summarized in three steps

Y=W(X)

Z=D(Y,λ)

$\hat{S} = \hat{w}$ (Z)

So the basic mehtod of image denoising is thresholing .By chooising a correct threshold , it is possible to remove most of the random noise[Jonathan Y. Stein(2000)].

<u>- The Haar Wavelet Transformation Algorithm</u>

The Haar wavelet transform is one of the simplest and basic transformations from the space domain to a local frequency domain. Haar wavelets are being used for the image transformation technique proposed here. To get an idea about the implementation of this wavelet , a simple example used to illustrate this , assume a one dimensional image with an eight pixel resolution, where the pixels have the following values : 7 5 3 9 3 7 5 3

By appling the Haar wavelet transform this image can be represented in term of a low resolution image and a set of details coefficients. The transformed data coefficients are obtained by averaging two consecutive pixels, while the detail coefficients represent the difference between the average and one of the two consecutive pixels. So the above image will be represented as follows after the first cycle:

Transformed coefficients :6 6 5 4 Detail coeficients:1 –3 –2 1

Now the original image can be represented by a four pixel transformed image ((a+b)/2) after the first cycle and a four pixel image containing the detail coefficients ((a-b)/2). Recursively iterating this algorithm leads to an image that is reduced by a factor of two for each cycle.The detail coefficients are required to reconstruct the image. Reconstruction of the original image involves adding and subtracting the detail coefficients to and from the subsequent transformation coefficients for each cycle .During Reconstruction of the original image of the previous example, adding and subtracting the transformation and detail coefficients obtain the first pair of pixels [Colm Mulcahy(2004)].

In 2D wavelet transformation, structures are defined in 2-D and the transformation algorithm is applied in x direction first and then in the y-axis

- Thresholding

Threshold determination is an important question for denoising process. Small Threshold may yield a result close to the input , but the result may still be noisy . A large threshold on the other hand , produces an output with large number of zero coefficients.This leads to a smooth image. Paying too much attention to smoothness, however ,destroys detials and in image processing may cause blur and artifacts[[Pujita Pinnamaneni(2003)].

The plot in fig (3) shows a noisy signal, for this signal replacing noisy coefficients(small coefficients below a certain threshold value)by zero and an inverse wavelet transform may lead to reconstruction that has denoised. Stated more precisely ,the thresholding idea based on the following assumptions[Gabriel Cristobal 1996]:

- The decorrelating property of a wavelet transform creates a sparse signal: most untouched cofficients are zero or close to zero.
- Noise is spread out equally along all coefficients
- The noise level is not too high so that the signal wavelet coefficients from the noisy ones can be distinguished [Martin Vetterli S Grace Chang, Bin Yu(2000)].

- Hard and Soft Thresholding

Hard and soft thresholding with threshold λ are defined as follows

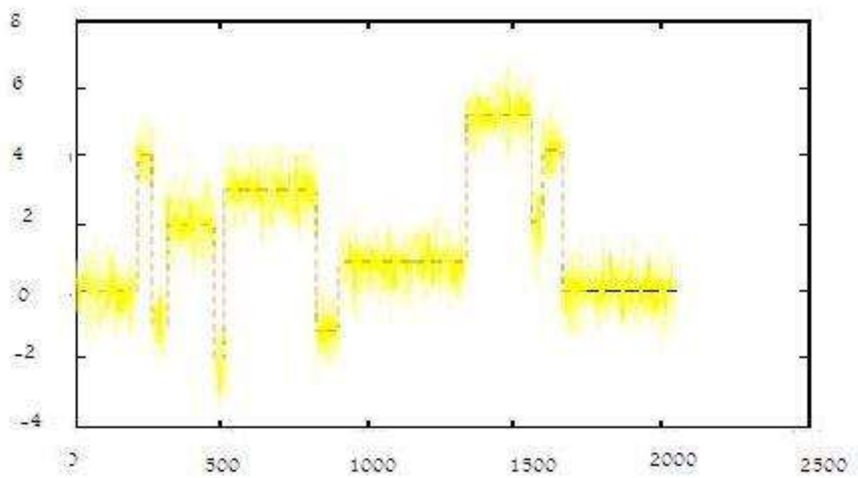
The hard thresholding operator is defined as

$$D(U, \lambda)=U \text{ for all } |U| > \lambda$$
$$=0 \text{ otherwise}$$

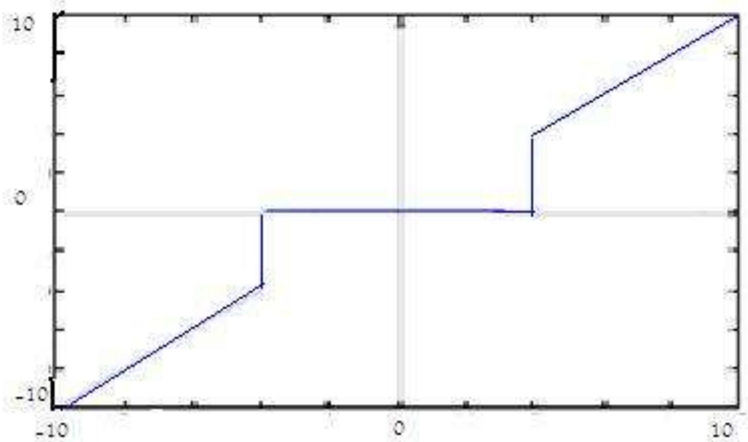
The soft thresholding operator on the other hand is defined as

$D(U, \lambda)=sng(U)\ max\ (o,|U|- \lambda)$

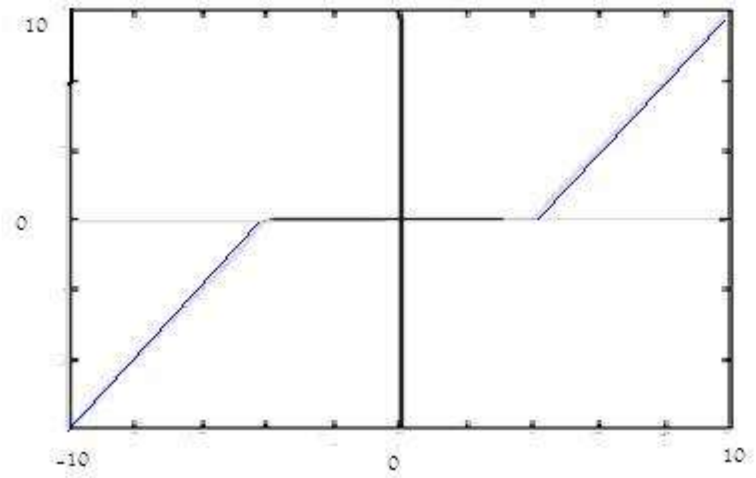
Hard threshold is a" keep or kill" procedure and is more intuitively appealing. The transform function is shown in fig (4).The alternative ,soft thresholding (whose transfer function is shown in fig(5)), shrinks coefficients above the threshold in absolute value.While at first sight hard thresholding may seem to be natural, the continuity of soft thresholding has some advantages. It makes algorthims mathematically more tractable.Moreover, hard thresholding does not even work with some algorithms , sometimes, pure noise coefficients may pass the hard threshold and appear as annoying 'blips' in the output.Soft thresholding shrinks these false structures[Maarten Jansen(2001)].



Fig(3) Noisy signal



Fig(4)Hard threshold



Fig(5) Soft threshod

IMPLEMENTION and RESULTS

In this paper the(Mathlab 7) program used to for image denoising according to following steps:

- Read RGB image
- Used the flowchat in Fig (2) to extact PC bands
- Define the throshold value, two type of throshold value used the hard throshold and the soft throshold
- The Haar transform matrix used to handle the PC1 using the block process operation that found in the Mathlab
- Get RGB band from the PC bands from following

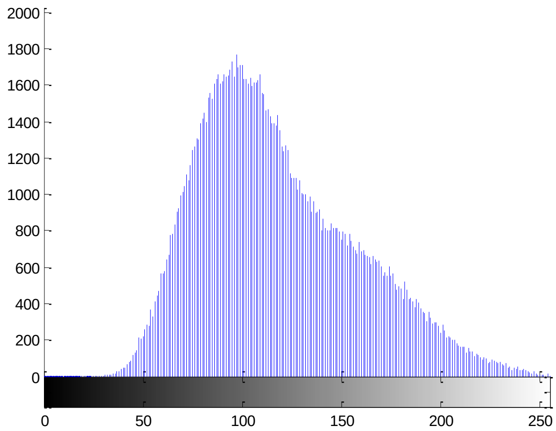
$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = E^{-1}_{(i,j)} * \begin{bmatrix} PC1' \\ PC2 \\ PC3 \end{bmatrix}$$

Where $PC1'$ is the processed band

$E^{-1}_{(i,j)}$ is the (3*3) eign vector matrix inverse

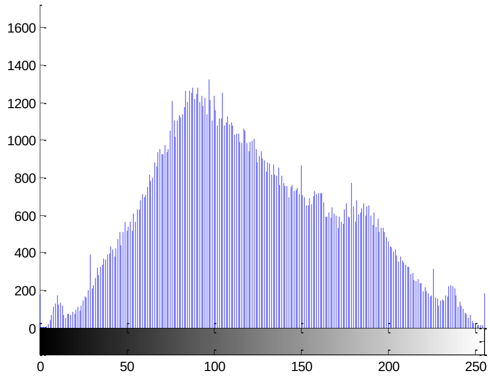
Fig(6) shows the result obtained when denoising sheme(Haar Wavelet)is applied to the noisy sattelite image(PC1 only)fig(5) using the hard threshold(zero threshold) and soft threshold (this threshold represent the stander devation and the mean of image PC1 gray values).

Fig(5-a) the orginal image



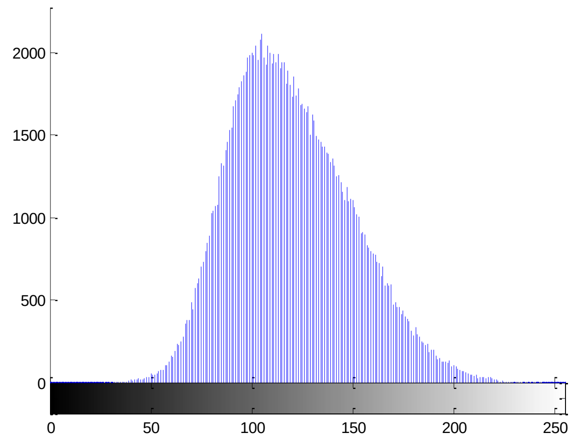
Fig(5-b)Original image histogram(PC1 only)

Fig(5-c) The noisy image



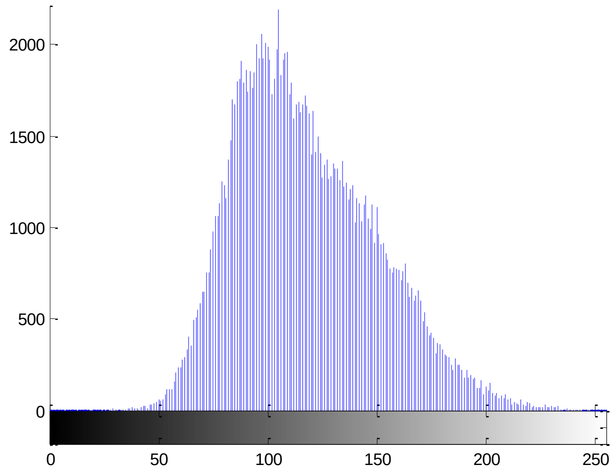
Fig(5-d)Noisy image histogram(PC1 only)

Fig(6-a)Denoising image using standard devation threshold



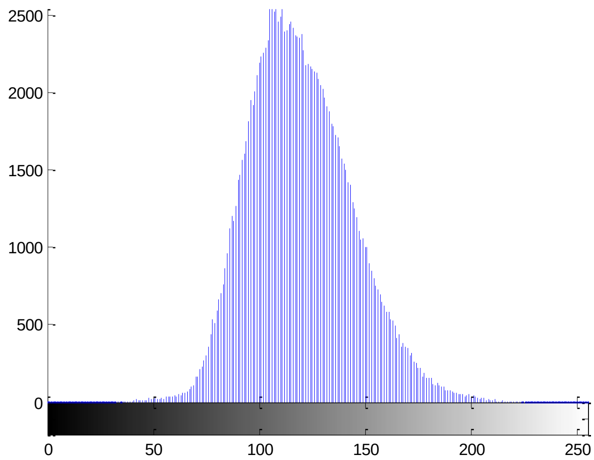
Fig(6-b)The Histogram of image (6-a)

Fig(6-c)Denoising image using mean threshold



Fig(6-d)The Histogram of image (6-c)

Fig(6-e)Denoising image using Hard threshold



Fig(6-f)The Histogram of image (6-e)

The effect of using wavelet denoising is clear ,by comparing the result images histograms with the original image histogram ,for example ,fig(6-f) shows the information losses (using hard threshold)comparing to fig(5-b), also the PSNR(Peak Signal to Noise Ratio) used to analysis and compare the Wavelet performance with standered method (a daptive wiener filter) .The PSNR defiend as folow

$$\text{PSNR}= 20\log_{10}\left(\frac{b}{rms}\right)$$

where b is the largest possible value of the signal (typically 255 or 1), and *rms* is the root mean square difference between two images. So by applying the a above equation the following result obtained

Image	PSNR
Noisy Image	20.24 dB
Wavelet denoising (standard devation threshold)	26.71 dB
Wavelet denoising (mean threshold)	26.78 dB
Wavelet denoising (hard threshold)	26.55 dB
Adaptive filter	25.87 dB

CONCLUSION and FUTURE WORK

Experimental results shown above(the PSNR values) indicates that wavelet transform is an effective method of denoising noisy images and the most important feature is the transform threshold choicing by investigating Soft threshold schemes virses the Hard threshold shemes.

The principal component transformation, is applied to the color image. The data histogram for the PC1 band is studied and compare with the one of the origional histogram and was found that approixamtly 90% of image information found in this band ,so by process the first component (PC1) only the time and storage need for color image processing can be reduced.

In future handle the same process using another methods of threshold technique such as SureShrink,VisuShrink and BayesShrink[Raghuram Rangarajan(2002)].

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