Wavelet approach for detecting clouds and their shadows

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Abstract—This Survey focuses on detection of clouds and their shadows applying wavelet approach. Wavelet method is based on the analysis of the energy of the image. Lastly, the wavelet image fusion is applied to fill the missing information the wavelet approach is applied to detect clouds and their shadows and subsequently fill out the missing information of the satellite images.

I. INTRODUCTION

Many conventional methods for removing clouds and their shadows from images are based on time series, but methods that use spatial information [7-13] result in better estimates. Methods including both spatial and temporal information performed better, by a slight margin, while a stratified approach produced less reliable estimates. A relatively new approach for dealing with the cloud contamination of a remotely sensed time series has been developed using the non-linear wavelet regression. This method can detect and estimate clouded areas at the same time at any point of the time series. The wavelet approach predicts the reference values for clouded areas better than other approaches did, and performs almost equivalent to linear prediction in shadowed areas

Signal processing, image analysis and data compressions are the principle fields of application of the wavelet. Extracting objects with the application of wavelet based analysis from laser scanning data reveals some difficulties but rest results proved that wavelet analysis has good potential for object extraction in simpler cases.

A number of alternatives can be considered:

1. Continuous Wavelet Transformation (CWT)
2. Discrete Wavelet Transformation (DWT)
3. Discrete Dyadic Wavelet Transformation (DDWT)
4. Stationary Wavelet Transformation (SWT)
5. Discrete Wavelet Frames (DWF)
6. Non –Separable Wavelet Frame (NWF)
7. Wavelet Packets (WP)

Here the three principle steps: pre-processing, processing and evaluation step are major methods.

II. REVIEW ON DATA AND THEORY OF METHODS

A. Review

The main objective of this paper is to explore the possibilities of the wavelet analysis to solve the problem of missing information caused by cloud cover in satellite images. Detection of clouds and their shadows and the processes for filling out the missing information we are using wavelet Transformation.

B. WAVELET THEORY

Short time Fourier transform, Wigner distributions, Radon transform, Fourier transform, and wavelet transform these are the some of the techniques of signal transforms. In order to understand what wavelet transformation is, let's take a look at the most common transformations.

1. Fourier Transform (FT)

Fourier transform is a mathematical technique for transforming a time-based signal into a frequency-based signal. It breaks down a signal into constituent sinusoids of different frequencies.

FT has an important disadvantage. In the process to transform a signal from time-amplitude representation to frequency domain representation, time information is lost. For that reason it is not possible to say when an event occurred. But FT is a reversible transform, that is, it allows going back and forth between raw and transformed signals.

FT decomposes a signal as the linear combination of two basic functions sine and cosine, with different amplitude phase and frequencies:

$$F(w) = \int_{-\infty} f(t) \cos(wt)dt + j \int_{-\infty} f(t)\sin(wt)dt \qquad (1)$$

In exponential form it can be expressed as equation 3 that represents the Fourier Transform of f(t), and equation 4 represent the inverse Fourier Transform of F(w):

$$F(w) = \int_{-\infty} f(t)\, e^{-2j\Pi wt} dt \qquad (2)$$

Where t represents time, w represents frequency, f denotes the signal in time domain and F denotes the signal in frequency domain. Time frequency representations are short-time Fourier Transform, Wigner distributions and our Wavelet transform.

2. Short-TimeFourier Transform(STFT)

To solve FT problem in time is analyze only a section of the signal at a time. This is called windowing the signal. It maps a signal into two-dimensional functions of time and frequency. This provides information about when and at what frequency an event occurs. But this transformation is limited by the size of the window.

3. *Wavelet Transform (WT)*

WT is an alternative to the STFT and is capable to provide the time and frequency representation of the signal through a process called decomposition. Decomposition is done Passing the time-domain signal through various high pass filters, which filter low frequency portions of the signal. The previous process is repeated several times and each time some frequencies are removed from the signal. Decomposition continues until the signal has been decomposed to a certain pre-defined level. After that process it is possible to obtain many signals (which represent the raw signal) but all corresponding to different frequency bands. If we plot those signals on a 3-D graph, we will have time in one axis, frequency in the second and amplitude in the third axes. WT does not use time-frequency but it uses time-scale region. Scale is inverse of frequency.

In one-dimensional context, we define the wavelet Ψ from the associated scaling function ϕ Wavelet function satisfy the following conditions.

The integral of Ψ is zero.

$$\int \Psi(x)\, dx = 0 \qquad (3)$$

The integral of ϕ is 1

$$\int \phi(x)\, dx = 0 \qquad (4)$$

In two-dimensional context, wavelets are defined as tensor product of one-dimensional wavelets: $\phi(x,y)= \phi(x)\ \phi(y)$ In the scaling function and $\Psi1(x,y)= \phi(x)(y)$, $\Psi2\ (x,y)= \Psi\ (x)\ \phi(y)$, $\Psi3\ (x,y) = \Psi(x)\ \Psi(y)$ are the three wavelets details.

4. Continuous Wavelet Transform (CWT)

The sum over the whole time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ. This process produces wavelet coefficients that are a function of scale and position.

$$C(scale,position) = \int f(t)\ \Psi(scale,position,t)dt \quad (5)$$

Scaling a wavelet simply means stretching (or compressing) it. If is done keeping the shape while changing the one-dimensional time scale a (a>0), Shifting a wavelet simply means delaying its onset. In other words, move the basic shape from one side to the other. Translating it to position b

$$1/\Gamma a\ \Psi(x/a) \quad (6)$$

$$\Psi(x-b) \quad (7)$$

Then translation and change of scale in one-dimensional context is represented as follow (from 8 and 9)

$$\Psi_{a,b}(t) = 1/a\ \Psi((x-b)/a)\ ,\ a>0, b\in IR \quad (8)$$

Then continuous analysis is done using

$$C(a,b) = f(t)\ 1/a\Psi(\tfrac{x-b}{a})dt \quad (9)$$

Where $a\in R^{\{+\}}$-0 and $b\in IR$

5. Discrete Wavelet Transform (DWT)

DWT provides information enough for analysis and synthesis with an important reduction of computation time. A time-scale representation of a signal is obtained using filtering techniques. Filters of different cutoff frequencies are used at different scales. High pass filters to analyze low frequencies. After the signal passes through filters its resolution is changed by upsampling and Downsampling operations. Downsampling is to remove some of the samples of the signal and Upsampling is to add new samples to the signal. We will limit our choice of a and b values by using only the following dyadic discrete set for one-dimensional context:

$$(j,k) \in Z^{+} : a=2^{j,}\ b= 2^{j}=ka \quad (11)$$

Applying to 10 it is possible to obtain the discrete wavelet

$$\Psi_{j,k}(t)=2^{-j/2}\Psi(2^{-j}\ t-k) \quad (12)$$

Where $(j,k) \in Z$

DWT is obtained applying to 2.5

$$C_{j,k} = \int f(t)\ \Psi_{j,k}(t)dt \quad (13)$$

DWT decomposes the signal into a coarse approximation and detail information. DWT employs two sets of functions called scaling and wavelets functions. Both of them are related to low pass and high pass filters, respectively.

C. WAVELET RECONSTRUCTION

In wavelet reconstruction process coefficients obtained from wavelet decomposition are used. As we mentioned, wavelet analysis involves filtering and downsampling whereas synthesis involves upsampling and filtering.

Wavelet reconstruction is known as synthesis whereas the previous DWT decomposition process is called Analysis

D. IMAGE FUSION

General definition is “Image fusion is the combination of two or more different images to form a new image by using a certain algorithm”.

Most of definitions refer to data fusion like tools and means themselves. We can underline the following concept that puts an emphasis on the framework and on the fundamentals in the remote sensing. “Data fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It

aims at obtaining information of greater quality; the exact definition of 'greater quality' will depend upon the application."

There are three different levels to perform image fusion. They depend on the stage at which fusion takes place:

1) pixel 2) feature 3) decision level.

This paper is focused on wavelet image fusion. After the wavelet decomposition of an image, the coefficients play an important role determining the structure characteristics at a certain scale in a certain location. Two images of different spatial resolution are decomposed. A transformation model can be derived to determine the missing wavelet coefficients of the lower resolution image. Using this it is possible to create a synthetic image from the lower resolution image at the higher spatial resolution. The image contains the preserved spectral information with higher resolution, hence showing more spatial details.

III. DATA AND METHODS

a. DATA ACQUISITION

First of all a study area was selected. It is a mountainous regions affected by cloud coverage during all the year. For that reason it is very difficult to obtain low cloud coverage satellite images for that area. There are valley regions and hilly areas. Land used is very diverse. There are urban areas, intensive and extensive agriculture areas and natural reserves. In order to search images of study area the Land Processors DAAC (Distributed Active Archive Center) System Data Gateway was used.

b. RADIOMETRIC CORRECTIONS

It is a part of pre-processing stage, cosmetic corrections and atmospheric corrections are classified in this phase. These corrections are related to the influence of haze, sun angle and skylight.

- Stripping
- Haze correction
- Sun angle correction

c. GEOMETRIC CORRECTIONS

At this point of our survey, it is not necessary that the multi-temporal images have geographic coordinates. For that reason we registered the images taking into account the master images. All the images we registered using image to image registration. Polynomial first order geometric model was used. Eg Multi-temporal images

d. CLOUD DETECTION

The survey of amount of clouds, their patterns and type in low-resolution satellite image data is known as Nephanalysis. High clouds can be determined using thermal infrared satellite images. Hourly visible and thermal infrared imaged to assist in producing daily forecasts in satellite.

It is a specific task that can be done by using remote sensing imagery. Cloud contamination affects the DN values in visible (0.4mμ-0.7mμ) and infrared (0.4mμ-1.0mμ) region of the electromagnetic spectrum.

e. WAVELET IMAGE FUSION

Discrete wavelet Transformation (DWT) and Wavelet packages (WP) were used to fuse multi temporal city images of the same sensor. In wavelet package analysis, the details as well as the approximation can be split. First, only the low frequency part was fused. But better results were obtained fusing both the low frequency and the high frequency.

A scheme to remove clouds and their shadows from a Land sat TM image was proposed by Wang et al. First detection of clouds and shadows was achieved. After that, wavelet image fusion was performed in order to remove clouds and shadows detected in the previous procedure. Discrete Wavelet Frame (DWT) was adopted in this approach and if show good fusion result even if there is mis registration between the two co registered images. Only one-level wavelet decomposition is performed, because it is sufficient for this procedure.

Two ways of wavelet image fusion can be done for fused panchromatic and multispectral images: substitution and addition method. In the substitution method, some of the resolution levels are substituted by the sub-images corresponding to the panchromatic image. In the additive method some of the wavelet resolution levels of the panchromatic are added to the R, G and B bands of the multispectral image. The additive method shows better results than HIS and LHS (Lightness-Hue-Saturation) methods.

IV. IMPLEMENTATION

Many methodologies are available in detection of clouds and their shadows. But only wavelet approaches have

been used in remote sensing from the last year.

PATTERN RECOGNITION

Defects in a variety of real textures including machined surfaces, natural wood, sandpaper and textile fabrics were well detected. This research we discuss about the advantages of this approach in remote sensing images and for our specific task, cloud detection.

Wavelet Decomposition

Let f(x,y) be the input image of size MxN. f(x,y) also can be represented by $f_{LL}{}^{o}f(x,y)$.

At first level decomposition it is possible to obtain one smooth sub-image $f_{LH}(x',y')$, $f_{LH}(x',y')$, $f_{LH}(x',y')$, that represent horizontal, vertical, diagonal ldetails respectively.

If we decompose an image at resolution level j=1, decomposition of $f_{LH}(x',y')$, results in one smooth image $f_{LH}(x',y')$,and also detail sub-images $f_{LH}(x',y')$, $f_{LH}(x',y')$, $f_{LH}(x',y')$, that represent horizontal, vertical and diagonal details respectively. Each of size $(M/2^{j+1})x(N/2^{j+1})$.

Energy of the wavelets

Wavelet energy is the normalized sum of square of detailed wavelet transformation coefficients. Let J be the total number of decomposition levels. The energy of each decomposed sub-image is calculated as follows:

Energy of the smooth sub-image:

$$E_s^J = \Sigma\Sigma \{ f_{LL}^{(J)}(x,y) \}^2 \qquad (1)$$

Energy of the horizontal detail sub-image at level j:

$$E^j_h = \Sigma_x\Sigma_y\{f^{(j)}_{LH}(x,y)\}^2, \quad j=1,2,\ldots\ldots J \qquad (2)$$

Energy of the horizontal detail sub-image at level j:

$$E^j v = \Sigma_x\Sigma_y\{f^{(j)}_{HL}(x,y)\}^2, \quad j=1,2,\ldots\ldots J \qquad (3)$$

Energy of the horizontal detail sub-image at level j:

$$E^j_d = \Sigma_x\Sigma_y\{f^{(j)}_{HH}(x,y)\}^2, \quad j=1,2,\ldots\ldots J \qquad (4)$$

The total energy of the image f(x,y) in J multi-resolution levels is given by

$$E = E^j_s + \Sigma^j_{j=1}E^j_h + \Sigma^j_{j+1}E^j_v + \Sigma^j_{j+1}E^j_d \qquad (5)$$

The normalized energy of each decomposed sub-image is defined as:

Normalized energy of smooth image

$$E_s = E^j_s / E \qquad (6)$$

Normalized energy of horizontal detail sub-image.

$$E_H = E^j_h / E \qquad (7)$$

Normalized energy of horizontal detail sub-image.

$$E_V = E^j_v / E \qquad (8)$$

Normalized energy of horizontal detail sub-image.

$$E_D = E^j_d / E \qquad (9)$$

The sum of normalized energy of the smooth image and detail sub-images must be equal to 1.

$$E_S + E_H + E_V + E_D = 1 \qquad (10)$$

Always, the normalized energy E_s of an isotropic pattern is significantly larger than that of an oriented pattern. In isotropic patterns most part of the energy is concentrated in smooth image E_s. On the other hand, in oriented patterns part of the energy located in the detail sub-images.

In order to know which sub-images to choose in the reconstruction process, it is necessary to define a threshold T_s.

$$\hat{f}(x,y) = W^{-1}[f^{(j)}{}_{LL}], \qquad \text{if} \quad E_s > T_s \qquad (11)$$

Where $\hat{f}(x,y)$ is the restored image. If $E_s > T_s$ then the smooth image is chosen in the reconstruction process and it is an isotropic pattern. For texture with $E_s > T_s$, it is classified as an oriented pattern. Then detail sub-images with low normalized energy values should be included for reconstruction. That process allows us to eliminate prominent directional patterns (horizontal, vertical, and diagonal) and emphasize the local animosities. In cases of an image containing an oriented pattern in horizontal, vertical, diagonal directions, the three normalized energies E_H, EV, ED will have similar values. In this case the smooth image is selected for reconstruction. When $E_s > T_s$ it is necessary to define another threshold T_D:

$$\hat{F}_H(x,y) = \begin{cases} W^{-1}[f^{(3)}{}_{LL}] & \text{if } E_H/D_{max} < T_D \\ 0 & \text{otherwise} \end{cases}$$

$$\hat{F}_V(x,y) = \begin{cases} W^{-1}[f^{(3)}{}_{LL}] & \text{if } E_H/D_{max} < T_D \\ 0 & \text{otherwise} \end{cases}$$

$$\hat{F}_V(x,y) = \begin{cases} W^{-1}[f^{(3)}{}_{LL}] & \text{if } E_H/D_{max} < T_D \\ 0 & \text{otherwise} \end{cases}$$

In this research, threshold value T_S and T_D are empirically set at 0.95 and 0.33 respectively. Choosing T_S is not crucial because the mechanism of selection T_D allow an isotropic texture to use the smooth sub-image for reconstruction. We can use the energy corresponding to the average of the smooth energies.

NO WAVELET APPROACH

This approach takes into account at least two satellite images of the same area at different times. As a pre-processing condition, those images have to be co-registered. That process ensures that the same pixel in both images refers to the same area. Because images from the same but different time have different solar irradiation and atmospheric effects it is necessary to reduce those effects. It is done through a brightness correction process that was applied for this approach.

- Brightness correction
- Detection of clouds and their shadows

Filling Out Gaps Using WAVELET IMAGE FUSION

Different wavelet transformation methods have been applied. Image fusion [1-6] has been produced using wavelet packages, discrete wavelet frames and multi-band transformation. Non-separable wavelet frame (NWF) performed better than Discrete Wavelet Frame (DWF). All of them perform better than the Discrete Wavelet Transformation (DWT), In order to fill out the missing information caused by clouds and their shadows in the satellite images of the project, image fusion using wavelet approach was applied.

For this process, two co-registered images are select. In this case selected a cloud-free image as main image and a clouded image selected as reference image.

Stationary wavelet approach was applied to both images. The resulting sub-images have the same size as the original images. Results detection of clouds and their shadows have been recorded on the binary decision maps. By using the two maps, we integrated the stationary wavelet transform values of the complementary information for each pixel. As a result a fused image is constructed by performing an Inverse Stationary Wavelet Transformation (ISWT) based on the combined transform values.

The wavelet transform provides both spatial and frequency domain localization. The two binary decision maps are used to control a switch so that the complementary information corresponding to the cloud and shadow regions of the reference image is extracted from the main image and incorporated into the reference image.
First, the previous combined transform process was performed for the low frequency sub-images (LL). The three sub-images used in the ISWT were sub-images from the non-clouded image. After that, a final fusion image process was applied. This time all the four sub-images resulting from the first stationary wavelet transformation (LL, LH, HL, HH) ware used for the combined transform process.

V. RESULTS

We describe the results obtained after application of four different methodologies in order to detect clouds and their shadows. Two approaches apply wavelet domain and one does not apply wavelet approach. We analyze the results obtained using all clouds detection approaches were assessed using an Error Matrix.

A. Pattern Recognition

It was necessary to select a band of satellite images in order to apply wavelet transformation. This criteria used so that the band id having the high grey value representing clouds and their shadows relative to other bands. We are interested to use the visible bands in order to preserve the spatial resolution of the satellite images then Wavelet decomposition was applied to an image. Haar family wavelet was used at five decomposition levels.

B. No Wavelet Approach

We applied the detection of clouds and their shadows to two different images of the multi-temporal images. One of them is an image with clouds and shadows as a reference image and the other one is an image without clouds and shadows as a main image. The selection criteria to choose the main image was the fact that image do not have clouds. That allows us to detect only clouds and their shadows of reference images. In order to test this methodology we apply the clouds and shadows detection procedure using different images. This time both images contain clouds and shadows.

C. Filling Out Missing Information

Two other procedures were applied for image fusion using wavelets. Both of them used the approximation sub-images to replace the clouded areas. In the first procedure, the detail sub-images of the non-clouded images of the clouded images were used in the reconstruction. As we can see in the final results, clouds and their shadows have been removed. Clouds and shadows of the lower-right part of the image have been replaced and its shadows good results. It is possible to observe that there is still a thin white ring around the area where the clouds were originally. That occurs because cloud detection procedure did not detect the borders of the clouds. This is evident specially around smaller clouds. Images depend on the quality of the detection of the clouds and their shadows.

D. Assessing IMAGE FUSION

In this paper clouded areas of the original image have been filled in. Then it is better to compare our results of image fusion with another method for replacing clouded areas. A simple replacement method was performed to fill in the missing information in the original image. In a visible inspection, we can see in the simple replacement method, They are not matching smoothly in the image. Also, it is easy to identify the thin white rings around the areas where the clouds were originally. Those problems are avoided in the results using wavelet approaches.Quality indicators for assessing image fusion

During this research we used the statistics and correlation coefficients indicators. This statistic parameters between the original clouded image. Those parameters show that the histograms of the original image and overall results are very similar. Comparing the original image with the fused image, it is possible to find the degree of difference. Generally speaking, if the correlation coefficient of two images approaches to one, this means their correlation is very strong. As a conclusion, we can say that he best approach in this research was done combination of the approximation sub-images and the detail sub-images. After that the wavelet reconstruction process was performed.

VI.RESULT IMAGES

(a). Original Image

(b). Binary Image

(c). Binary Image after Morphological opening

(d). Binary Image after Morphological Opening-closing

(e). Eroded of Morphological open-closed binary image.

(f). Contour component Ic

(g). Residual component R

(h). Filled Contour component Fc

(i). Fc\Ic

(j). Reconstructed Image.

VI. CONCLUSION

Pattern recognition approach detected the clouds correctly and also some other objects were detected as clouds. Shadow detection had the equal properties in detection. Pattern Recognition approach could perform better in some areas with more homogeneous textures and regular patterns.

Wavelet approach bigger clouds were detected better than smaller clouds.

Results of the Image fusion step to fill in the missing information depending on the accurate detection of clouds and their shadows. Missing information is enhanced.

Wavelet approach is filing information in the clouded areas perform better.

REFERENCES

[1] Enhancement of Cloud-Associated Shadow Areas in Satellite Images Using Wavelet Image Fusion *A. Abd-Elrahman, I.F. Shaker, A.K 1 2 3 . Abdel-Gawad and 3A. Abdel-Wahab(2008)*

[2] Review of Shadow Detection and De-shadowing Methods in Remote Sensing, AmirReza SHAHTAHMASSEBI1, YANG Ning1, WANG Ke1, Nathan MOORE2, SHEN Zhangquan1 Vol no 23, pp. 403–420.

[3] Removing Shadows from Images, In Proc. of M.A. Abdelwahab, 2005. Toward Removing

[4] European Conf. on Computer Vision, 4: 823.836. Cloud and Shadow Effects in Satellite Images

[5] Zhou, G., Z. Qin, S. Benjamin and W. Schickler, 2003. Technical Problems of Deploying National Urban Large-scale True Orthoimage Generation. The 2nd Digital Government Conference, Boston, May 18-21, 2003, pp: 383-3871.

[6] Simpson J J, Sitt J R, 1998. A procedure for the detection and removal of cloud shadow from AVHRR data over land. *IEEE Transactions on Geoscience and Remote Sensing*, 36(3): 880–897.doi: 10.1109/36.673680

[7] Saka Kezia, Dr.I.Santi Prabha, Dr.V.VijayaKumar, "A New Texture Segmentation Approach for Medical Images", International Journal of Scientific & Engineering Research, Vol. 4, No. 1, pp.1-5, January 2013.

[8] Saka Kezia, Dr.I.Santi Prabha, Dr.V.VijayaKumar, "Innovative Segmentation Approach Based on LRTM", International Journal of Soft Computing and Engineering, Vol. 2, No. 5, pp. 229-233, November 2012.

[9] Saka Kezia, Dr.I.Santi Prabha, Dr.V.VijayaKumar, "A Color-Texture Based Segmentation Method to Extract Object from Background", International Journal Image, Graphics and Signal Processing, Vol. 5, No. 3, pp.19-25, March 2013.

[10] Saka Kezia, Dr.V.VijayaKumar, Dr.I.Santi Prabha, "Auto Detection of Tubercle Bacilli Based on Wavelets", International Journal on Graphics Vision and Image Processing, Vol. 11, No. 3, pp.980-986, June 2011.

[11] M.Joseph Prakash, Saka.Kezia, Dr.I.Santi Prabha, Dr.V.Vijaya Kumar, "A New Approach for Texture Segmentation using Gray Level Textons", International Journal of Signal and Image Processing, Vol. 6, No. 3, June 2013 (Accepted).

[12] M.Joseph Prakash, Saka.Kezia, Dr.I.Santi Prabha, Dr.V.Vijaya Kumar, "An Approach for Texture Segmentation based on Random Field Model and Wavelet Fusion", Vol. 1, No. 3, pp. 183-189, May 2010.

[13] M.Joseph Prakash, Saka Kezia, Dr.I.Santi Prabha, Dr.V.Vijaya Kumar, "A Novel Approach for Texture Segmentation Based on Rotationally Invariant Patterns", International Journal of Computer Engineering & Sciences, Vol.2, No.2,pp.1-8,Jan 2013.