Missing information in Remote Sensing: Wavelet approach to detect and remove clouds and their shadows
Missing information in Remote Sensing: Wavelet approach to detect and remove clouds and their shadows

by

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Abstract

In this research the wavelet transform was applied to detect clouds and their shadows and subsequently fill out the missing information in a multi-temporal set of Aster images of the north area of Ecuador.

Wavelet theory is a powerful mathematical tool recently developed for signal processing. Remote sensing images can be considered as a signal. Furthermore, the wavelet transform is related to the concept of multi-resolution analysis where image are decomposed into successive scales or spatial resolutions.

The first part of this research focuses on the detection of clouds and their shadows, applying three different methods involving wavelets and one non-wavelet approach. The first wavelet method was based on analysis of the energy or the wavelets for a pattern recognition approach. The second method used a stationary wavelet approach, the third method as well, but in a multi-scale product. Comparing the four methods, wavelet approaches did not perform better than the non-wavelet approach.

In the second part of this research, wavelet image fusion was used to fill in the missing information and then the results were evaluated.

Keywords
Wavelets, clouds detection, image fusion, Ecuador, Satellite images
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Chapter 1
Introduction

1.1 Abstract

A significant obstacle to extracting information using remote sensing imagery is the presence of clouds and their shadows. Various approaches have been tried to solve this problem with differing results. Wavelet transformation has showed to be a useful tool to deal with clouds and shadows coverage in remote sensing images. This research proposal focuses on the application of wavelet transformation in order to detect clouds and their shadow. After that fill out the missing information is perform using a wavelet fusion approach. This method will be tested on images from the upper zone of Mira watershed in the Carchi and Imbabura provinces in the Andean mountain region of north Ecuador.

1.2 Background

A significant obstacle for extracting information from remote sensing imagery is the missing information caused by clouds and their shadows in the images. According to a study by A. P. Hoeke in 1986, the average percentage of cloud cover in the equatorial region is in order of 75% [26]. Leemans and Cramer in 1991 reported climate statistics showing that northwestern Europe during the least clouded months still has cloud coverage of about 40% [2].

There are some radar satellites that do not have cloud contamination problems because they operate in the microwave range of the electromagnetic spectrum. It is possible to obtain microwave imagery information from some of the satellites that goes back in time to 1991. But these kinds of images cannot replace information provided by optical remote sensing data. The emitted radiation in microwave range is very low while in the visible range the maximum energy is emitted. Consequently, in order to obtain imagery in the microwave region and measure these signals, which are weak, large areas are imaged. This results in relatively poor spatial resolution [14]. On the other hand, by contrast, images in the visible range have a high resolution.

The problem of missing information caused by clouds and their shadows has
been studied in many situations and there now exist a number of methodologies to address this problem. One of the approaches that has been used involves image fusion techniques. These techniques combine Radar images and data from optical sensors in the clouded areas. For instance, a study done in Indonesia illustrated the feasibility of image mapping for updating topographical maps at 1:100,000 scales using multisensor data [26].

Many conventional methods for removing clouds and their shadows from images are based on time series, but methods that use spatial information result in significantly better estimates. Methods including both spatial and temporal information performed better, by a slight margin, while a stratified approach produced less reliable estimates [2].

A common method for replacing clouded pixels by land cover reflection estimates is the Maximum Value Composite, which is mainly applied to NDVI composite. From a ten-day time series the maximum NDVI value per pixel is taken to compose a new image. Others methods that also use temporal information are Minimum Value Composite and Simple Replacement.

Spatial information is used by geostatistical methods like Ordinary Kriging and Stratified Kriging. Moreover, a combination of spatial and temporal domain is used by Ordinary co-Kriging and Stratified co-Kriging. The application of these methods (temporal, spatial, and temporal and spatial) to NOAA-AVRR images has revealed that co-Kriging is the best alternative. In cases where co-Kriging is not possible, a viable alternative is found in ordinary Kriging. RMSE values are somewhat higher with ordinary Kriging, but this method has the advantage of not needing a second image as co-variable [2].

A relatively new approach for dealing with the cloud contamination of a remotely sensed time series has been developed using the robust nonlinear 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 that all other approaches did, and performs almost equivalent to linear prediction in shadowed areas [8].

The wavelet analysis is a refinement of the Fourier analysis. Fourier analysis is based on the description of an input signal (or function) in terms of its frequency components. It can select frequencies from a signal consisting of many frequencies. However, the disadvantage of this analysis is that it cannot deal with a signal that is changing over time. On the other hand, wavelet analysis can deal with the amount of localization in time and in frequency. A narrow time window is needed to examine high-frequency content, but a wide time window is allowed when investigating low-frequency components [24].

Signal processing, image analysis and data compression are the principal fields of application of the wavelet. Extracting objects with the application of wavelet-based analysis from laser scanning data revealed some difficulties but
test results proved that wavelet analysis has good potential for object extraction in simpler cases [4].

In order to experiment with wavelet transformation a number of alternatives can be considered:

- Continuous wavelet transformation (CWT)
- Discrete wavelet transformation (DWT)
- Discrete dyadic wavelet transformation (DDWT)
- Stationary wavelet transformation (SWT)
- Discrete wavelet frames (DWF)
- Non-separable wavelet frame (NWF)
- Wavelet packets (WP)

1.3 Objectives

The main objective of this research is to explore the possibilities of the wavelet analysis to solve the problem of missing information caused by cloud cover in satellite images. The main objective can be split into the following sub-objectives:

- Review the techniques currently used for detection of clouds and their shadows and the processes for filling out missing information using wavelet transformation.
- Try a number of wavelet transformation alternatives to detect clouds and their shadows.
- Compare the performance of wavelet approaches and a non-wavelet approach for the detection of clouds and their shadows.
- Compare the performance of the clouds and their shadows detection using wavelet approaches with the results of clouds and their shadows detection using a non-wavelet approach.
- Explore and perform wavelet transformations to fill out missing information caused by clouds and their shadows.
- Evaluate the results of the filling out missing information procedures.

Not all the wavelet transformation alternatives will be tested. Only the alternatives that present a viable approach will be considered.
1.4 Research Questions

In order to achieve the research objective the following research questions have been defined to serve as guidelines:

- Is wavelet transformation a good alternative to solve the problem of missing information caused by clouds and shadows in remote sensing images?
- Which would be a good wavelet alternative to detect clouds and their shadows in remote sensing images?
- Does the detection of clouds and their shadows using wavelet transformation perform better than other approaches that do not use wavelet transformation?
- Is wavelet transformation a viable alternative to fill out missing information caused by clouds and their shadows in remote sensing images?

1.5 Methodology

The methodology of this research has three principal steps: pre-processing, processing and evaluation steps.

1.5.1 Pre-processing

- Aster image acquisition: It was possible to obtain a number of ASTER satellite images through ITC. Those satellite images correspond of the upper zone of the Mira watershed in the north area of Ecuador.
- Image selection: Selecting the same subset area in 7 selected images. This is done in order to have a multi-temporal data set of the study area.
- Atmospheric corrections: It is necessary to apply atmospheric corrections. Striping, Haze and sun angle corrections are applied to the multi-temporal data set.
- Geometric corrections: Those are applied to all images of the data set, by using the information in the metadata files. The accuracy of the process can then be determined. If the level of accuracy is insufficient, it will be necessary to select a principal image of the data set, then co-register the other images with respect to the principal image. This is an image-to-image process.

1.5.2 Processing

- Band selection: Aster images have 14 bands. We are interested in using the higher spatial resolution of the ASTER satellite image. Then, it is necessary to choose a band of the VNIR set, since the other sets have lower resolution.
Chapter 1. Introduction

• Apply wavelet transformation through pattern recognition approach in order to detect clouds and their shadows.

• Use a Stationary wavelet transformation to detect clouds and their shadows.

• Detection of clouds and their shadows using multi-scale information of the wavelet.

• Apply a no-wavelet approach to detect clouds and their shadows.

• Compare the results of all previous clouds– and shadows detection.

• Perform an image fusion procedure to fill out missing information caused by clouds and their shadows.

1.5.3 Evaluation

• Application of Error matrix to evaluate the accuracy of the clouds– and shadows detection.

• Evaluation of the procedure of filling out the missing information.

1.6 Resources

• Data: ASTER images are used on this research. A multitemporal data set of ASTER images at Level–1A is selected. The study area is located in the north area of Ecuador. It is a mountainous region of Carchi and Imbabura provinces. In this area the non-governamental organization RANDI-RANDI has been implemented research projects with the support of Canada’s International Development Research Center (IDRC).

• Software: MATLAB software-package version 6.5.1 with Wavelet Tool application module. Image processing ERDAS 8.6 and ILWIS 3.12.

• Publications and books related with the topic.

• Internet resources

1.7 Structure of the thesis

• Chapter 1. Introduction; it describes an overview of thesis work. It states the problem and outlines the prior work, research objectives, research questions, resources and thesis structure.

• Chapter 2. Literature review; this chapter gives a review of the ASTER image data and a introductory part of the wavelet theory, wavelet transformation, two dimensional decomposition and wavelet families.
• Chapter 3. Data and Methods; in this chapter the pre–processing is explained and some methods for cloud detection and image fusion area explained.

• Chapter 4. Implementation: it explains steps that were followed in the implementation procedure.

• Chapter 5. Results and Discussion; in this chapter the obtained results of implementation process are explained and discussed.

• Chapter 6. Conclusions and recommendations; summarizes the conclusions drawn from the research process, also gives some recommendations for further work.
2.1 ASTER Images

ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) is an advanced multispectral imager that was launched on board of NASA's Terra spacecraft in December of 1999.

The objective of ASTER Project is a better understanding of local and regional phenomena on the Earth surface and its atmosphere. More specific areas of scientific research include: ??

- geological and soil
- volcano monitoring
- carbon cycle and marine ecosystem
- aerosol and cloud studies
- evapotranspiration
- hydrology
- vegetation and ecosystem dynamics, and
- land surface climatology

Terra is a polar orbiting spacecraft. It is operated in a circular, near polar orbit at an altitude of 705 km (at equator). The orbit is sun-synchronous (descending) with a local time of 10:30 a.m. The repeat cycle is 16 days. Table 2.1 shows some Aster images specifications.

ASTER is an advanced multispectral imager. Its instruments cover a wide spectral region from the visible to the thermal infrared by 14 spectral bands each with high spatial, spectral and radiometric resolution. The spatial resolution varies with wavelength: 15 m in the visible and near-infrared (VNIR), 30 m in the short wave infrared (SWIR), and 90 m in the thermal infrared (TIR).
2.2. ASTER Level-1A

<table>
<thead>
<tr>
<th>Subsystem</th>
<th>Band No.</th>
<th>Spectral Range (mm)</th>
<th>Spatial Resolution (m)</th>
<th>Scanner</th>
</tr>
</thead>
<tbody>
<tr>
<td>VNIR</td>
<td>1</td>
<td>0.52–0.60</td>
<td>15</td>
<td>Pushbroom</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.63–0.69</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3N</td>
<td>0.78–0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3B</td>
<td>0.78–0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SWIR</td>
<td>4</td>
<td>1.60–1.70</td>
<td>30</td>
<td>Pushbroom</td>
</tr>
<tr>
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<td>5</td>
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<td>2.185–2.225</td>
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<td></td>
<td>8</td>
<td>2.295–2.365</td>
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<tr>
<td></td>
<td>9</td>
<td>2.360–2.430</td>
<td></td>
<td></td>
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<tr>
<td>TIR</td>
<td>10</td>
<td>8.125–8.475</td>
<td>90</td>
<td>Whiskbroom</td>
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<td></td>
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<td>10.25–10.95</td>
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<td></td>
<td>14</td>
<td>10.95–11.65</td>
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</table>

VNIR has three bands and a system with two telescopes. A nadir looking telescope and a backward looking telescope. They enable a stereoscopical view only for band 3. SWIR has six bands; and TIR has five bands. Each subsystem operates in a different spectral region with its own telescope(s). An ASTER scene cover 60 km by 60 km. [11]

2.2 ASTER Level-1A

In this research we will use Level-1A ASTER images. For that reason we focus on them and their characteristics.

The ASTER images have two types of Level-1 data: Level-1A and Level-1B data. Level-1A data are reconstructed, unprocessed instrument data at full resolution. Data consist of the image data, the radiometric coefficients, the geometric coefficients and other auxiliary data without applying the coefficients to the image data to maintain the original data values. The Level-1B data are generated by applying these coefficients for radiometric calibration and geometric resampling. Figure 2.1 shows a a general scheme of Level-1 data processing.

Panoramic correction has been considered in the geometric system correction process for all Aster images. Its takes into account three factors that have a geometric impact on the data. Those three factors are: change of the spacecraft orbit, change of the earth radius and topographic change. Panoramic effect can be considered. The swath $L_{ct}$ and pixel size change in cross track direction[10]. $L_{ct}$ is given by
Figure 2.1: Level-1 Data Processing General Scheme

\[ Lct = R\{\arcsin\{(R + H)/R \sin(\theta + \Delta\theta)\} - \arcsin\{(R + H)/R \sin(\theta + \Delta\theta)\} - 2\Delta\theta\} \]  

(2.1)

where
- \( R \): radius for local curvature of the earth
- \( H \): altitude of the spacecraft
- \( \theta \): look direction angle of the central pixel
- \( \Delta\theta \): look direction angle difference of the edge pixel from the direction \( \theta \)

### 2.3 Wavelet Theory

Many existing signals transforms are used for different applications like Hilbert transform, short-time Fourier transform, Wigner distributions, Radon-transform, Fourier transform, wavelet transform. In order to understand what is wavelet transformation, let’s take a look at one of the most common transformations, the Fourier Transformation.

#### 2.3.1 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
2.3. Wavelet Theory

sinusoids of different frequencies \[28\].

Most of the signals are time-domain in their raw format. When one plots these signals they are in time-amplitude representation. In other words plotting those signals one of the axes is time (independent variable), and the other is the amplitude (dependent variable). After the FT the signal is expressed in frequency spectrum. That is frequency will be represented as independent variable and amplitude will be expressed as dependent variable.

![Figure 2.2: Time amplitude representation and frequency spectrum](image)

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 to go back and forth between raw and transformed signals.

Depending on the type of application, many times it is not important to have information related with time. This occurs when a signal is stationary. In other words, the frequency of a signal does not change in time or there is only a minimal change and we know in advance how much the frequency changes with time. Sometimes the frequency of a signal that we need to analyse changes constantly with time. They are called non-stationary signals and FT is not a suitable technique in that case.

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

\[
F(\omega) = \int_{-\infty}^{\infty} f(t) \cos(\omega t) dt + j \int_{-\infty}^{\infty} f(t) \sin(\omega t) dt \tag{2.2}
\]

In exponential form it can be expressed as Equation 2.3 that represents the Fourier transform of \(f(t)\), and equation 2.4 represent the inverse Fourier transform of \(F(\omega)\):

\[
F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-2j\pi\omega t} dt \tag{2.3}
\]
\[ f(t) = \int_{-\infty}^{\infty} F(\omega) e^{2j\pi \omega t} \, d\omega \]  

(2.4)

where \( t \) represents time, \( \omega \) represents frequency, \( f \) denotes the signal in the time domain and \( F \) denotes the signal in the frequency domain.

Time frequency representation are short-time Fourier transform, Wigner distributions and our Wavelet transform.

2.3.2 Short-Time Fourier Transform (STFT)

One way to solve FT problem in time is analyse 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 information is limited by the size of the window.

The size of the window must be the same for all frequencies but many signals require a more flexible analysis.

2.3.3 Wavelet Transform (WT)

WT was developed as an alternative to the STFT and is capable to provide the time and frequency representation of the signal through a process called decomposition. This is done passing the time-domain signal through various high pass filters which filter out high frequency portions of the signal and low 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 [28].
2.3. Wavelet Theory

In reality WT does not use time-frequency but it uses time-scale region. Scale is inverse of frequency (high scale = low frequency and low scale = high frequency).

Using WT it is possible to know which spectral components exist at any time instant. But it is not possible to know which spectral component exists at any given time interval of time. Higher frequencies are better resolved in the time domain and lower frequencies are better resolved in the frequency domain.

![Wavelet Transformation](image)

Figure 2.4: Wavelet Transformation

In one-dimensional context, we define the wavelet $\psi$ from the associated scaling function $\phi$. Wavelet function satisfy the following conditions.

The integral of $\psi$ is zero.

$$\int \psi(x)dx = 0$$  \hspace{1cm} (2.5)

The integral of $\phi$ is 1.

$$\int \phi(x)dx = 1$$  \hspace{1cm} (2.6)

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 $\psi_1(x, y) = \phi(x)\psi(y)$, $\psi_2(x, y) = \psi(x)\phi(y)$, $\psi_3(x, y) = \psi(x)\psi(y)$ are the three wavelets details.

**Continuous Wavelet Transform (CWT)**

The CWT is the sum over the whole time of the signal multiplied by scaled, shifted versions of the wavelet function $\psi$. This process produces wavelets coefficients that are a function of scale and position.

$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)dt$$  \hspace{1cm} (2.7)

Scaling a wavelet simply means stretching (or compressing) it. It is done keeping the shape while changing the one-dimensional time scale $a$ ($a > 0$).
Chapter 2. Literature Review

\( \frac{1}{\sqrt{a}} \psi \left( \frac{x}{a} \right) \) \hspace{1cm} (2.8)

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 \( b \)

\[ \psi(x - b) \] \hspace{1cm} (2.9)

Then translation and change of scale in one-dimensional context is represented as follow (from 2.8 and 2.9)

\[ \psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left( \frac{x - b}{a} \right), \quad a > 0, b \in \mathbb{R} \] \hspace{1cm} (2.10)

Then Continuous analysis is done using

\[ C(a, b) = \int_{\mathbb{R}} f(t) \frac{1}{\sqrt{a}} \psi \left( \frac{x - b}{a} \right) dt \] \hspace{1cm} (2.11)

where \( a \in R^{(+) - 0} \) and \( b \in \mathbb{R} \)

**Discrete Wavelet Transform (DWT)**

Information provided by CWT is highly redundant as far as the reconstruction of the signal is concerned. 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 are used to analyse high frequencies and low pass filters to analyse 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:

\[ (j, k) \in Z^2 : a = 2^j, b = k2^j = ka \] \hspace{1cm} (2.12)

Applying to 2.10 it is possible to obtain the discrete wavelet

\[ \psi_{j,k}(t) = 2^{-j/2} \psi(2^{-j} t - k) \] \hspace{1cm} (2.13)

where \( (j, k) \in Z \)

DWT is obtained applying to 2.5

\[ C_{j,k} = \int_{-\alpha}^{+\alpha} f(t) \psi_{j,k}(t) dt \] \hspace{1cm} (2.14)

DWT decomposes the signal into a coarse approximation and detail information. DWT employs two sets of functions called scaling and wavelet functions.
2.3. Wavelet Theory

Both of them are related to low pass and high pass filters, respectively. Figure 2.5 shows the DWT process.

![Figure 2.5: Discrete Wavelet Transformation](image)

The DWT process can be iterated with successive approximations. The original signal is broken down into many lower resolutions. This process is called *multi-level wavelet analysis*. Figure 2.6 shows this process.

![Figure 2.6: Multi-Level wavelet analysis](image)

**Wavelet Reconstruction**

Wavelet reconstruction is known as *synthesis* whereas the previous DWT decomposition process is called *analysis*. In wavelet reconstruction process coefficients obtained from wavelet decomposition are used. As we mentioned, wavelet analysis involves filtering and downsampling whereas wavelets synthesis involves upsampling and filtering.

The low and high pass filters (L and H), together with their associated reconstruction filters (L’ and H’), form a system called *quadrature mirror filters*.
Chapter 2. Literature Review

Two-Dimensional Decomposition

As we saw before, one-dimensional wavelet analysis is based on one scaling function $\varphi$ and one wavelet function $\psi$. For images, a similar algorithm is possible for two-dimensional wavelets and scaling functions obtained from one-dimensional wavelets by tensorial product. These wavelets functions are the simple product of one-dimensional wavelet function, in horizontal, $x$ and vertical direction, $y$.

Considering a digital image of size $M \times N$ pixels in the horizontal and vertical direction respectively. This image is denoted by $F(x, y)$, with the same spatial resolution $r$ in both directions [9].

Two-dimensional decomposition is the product of two processes where each row of the matrix (image) is considered a one-dimensional signal. The first step consists of applying filters $H$ and $L$ to each row of the matrix. The result are two matrices with the same number of rows but half as many columns as the original image. Each of this matrices is considered as consisting of columns of one-dimensional signals. Filters $H$ and $L$ are applied to the columns. The result of that process are four square matrices, each with half as many rows and half as many columns as the original image. The four results matrices (images) are the scaling function and the three wavelets functions. Figures 2.8 describes two-dimensional decomposition.

The matrix $C_{j-1}$ is a "smoothing" image of the higher level scaling coefficients. Matrices $D_{j-1}^1, D_{j-1}^2, D_{j-1}^3$ represent the horizontal, vertical and diagonal details, respectively [24]. Figure 2.9

Two-dimensional discrete wavelet decomposition produces a decomposition of approximation coefficients at level $j$ in four components: the approximations at level $j + 1$ and details in three directional orientations (horizontal, vertical and diagonal). The following figure 2.10 resumes the basic decomposition and
2.3. Wavelet Theory

There are different types of wavelet families, each of them having different characteristics. Table 2.2 lists some of the wavelet families.
Chapter 2. Literature Review

Figure 2.10: Two-dimensional decomposition and reconstruction steps

Table 2.2: Wavelet families

<table>
<thead>
<tr>
<th>Wavelet Family</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar wavelet</td>
</tr>
<tr>
<td>Daubechies wavelets</td>
</tr>
<tr>
<td>Symlets</td>
</tr>
<tr>
<td>Coiflets</td>
</tr>
<tr>
<td>Biorthogonal wavelets</td>
</tr>
<tr>
<td>Reverse biorthogonal wavelets</td>
</tr>
<tr>
<td>Meyer wavelets</td>
</tr>
<tr>
<td>Discrete approximation of Meyer wavelet</td>
</tr>
<tr>
<td>Gaussian wavelets</td>
</tr>
<tr>
<td>Mexican hat wavelet</td>
</tr>
<tr>
<td>Morlet wavelet</td>
</tr>
<tr>
<td>Complex Gaussian wavelets</td>
</tr>
<tr>
<td>Shannon wavelets</td>
</tr>
<tr>
<td>Frequency B-Spline wavelets</td>
</tr>
<tr>
<td>Complex Morlet wavelets</td>
</tr>
</tbody>
</table>

**Haar wavelet**

Haar wavelet is the simplest wavelet family. The Haar function is given by:

\[
\psi(x) = \begin{cases} 
1, & 0 \leq x < \frac{1}{2} \\
-1, & \frac{1}{2} \leq x < 1 \\
0, & \text{otherwise}
\end{cases}
\]

The previous Haar function is called *mother wavelet*. Mother wavelet is a source of an entire family of wavelets by means of two operations: dyadic dilations and integer translations. Let \( j \) denote the dilation index and \( k \) represent the translation index, we will obtain 2.13 [24].
Filters used by Haar wavelet take advantage of the relationship between neighbouring elements:

\[
a = \frac{X_{2i} + X_{2i+1}}{2} \quad \text{(2.15)}
\]

\[
d = X_{2i+1} - X_{2i} \quad \text{(2.16)}
\]

Equation 2.15 represents the average of adjacent elements. While equation 2.16 represents the difference between adjacent elements.

In this research we will explore the advantages of Haar wavelet family to detect clouds and their shadows. Also in the final procedure of this research we will use Haar wavelet family for image fusion procedure in order to fill out missing information.

2.4 Image Fusion

There are many definitions of image fusion in the remote sensing field. A general definition is "Image fusion is the combination of two or more different images to form a new image by using a certain algorithm" [26].

Words like 'data' and 'image' have a similar meaning. Often not only remote sensing images are fused but also other spatial data like GPS coordinates and topographic maps, etc.

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 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." [39]

Image fusion has been used to combine high spatial resolution, panchromatic imagery, with multispectral imagery of low resolution. In this way, the high spatial resolution is incorporated to the spectral resolution. Also it is possible to fuse images of the same sensor but with different spatial resolution (e.g. lower resolution of thermal bands of TM imagery can be enhanced using the higher resolution bands). Fusion of the SAR/VIR has showed good results to replace the clouds and their shadows using the advantage of SAR images for penetrating clouds [27].

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.

Image fusion at pixel level means fusion at the lowest level referring to the merging of measured physical parameters. It uses raster data that is at least
co-registered but most commonly geocoded. The following approaches are used to produce image fusion at pixel level:

- RGB colour composites;
- Intensity Hue Saturation (IHS) transformation;
- Lightness-Hue-Saturation (LHS)
- Arithmetic combinations;
- Principal components analysis;
- Wavelets;
- Regression variable substitution;
- Combination of techniques.

A distinction has to be made between the pure visual enhancement (superimposition) and real interpolation of data to achieve higher resolution (e.g. wavelets) [26].

This research 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 [26].
2.4. Image Fusion
Chapter 3

Data and Methods

3.1 Data Acquisition

First of all a study area was selected. It is in the north part of Ecuador. Specifically, it is located in the Mira watershed that is in Carchi and Imbabura provinces. That is a mountainous region affected by cloud coverage during all year. Clouds coming from Amazonas forest (East) and Pacific Ocean (west) meet over that area. For that reason it is very difficult to obtain low cloud coverage satellite images for that area. Many Governamental and no-governamental organizations are working on that area but there is not enough information coming from remote sensing sources.

The study area is a very heterogeneous area. There are valley regions and hilly areas. Land use is very diverse. There are urban areas, intensive and extensive agriculture areas and natural reserves.

In order to search images of the study area the Land Processes DAAC (Distributed Active Archive Center) System Data Gateway was used. This Center was established as part of NASA’s Earth Observing System (EOS) Data and Information System (EOSDIS) initiative to process, archive and distribute land–related data collected by EOS sensors.

The archive contained 37 ASTER satellite images Level-1A of the study area. This selection was done based on the image quality (cloud coverage and area of interest). A subset (512 pixels x 512 pixels) without a large amount of cloud coverage was selected. Then the final selection of images was done and they are displayed in Table 3.1

3.2 Importing images

All images were imported using ERDAS. Then it was possible to select the images that have overlapping areas.
3.3 Radiometric corrections

Radiometric corrections is part of the pre-processing stage. It consists of cosmetic corrections and atmospheric corrections. Cosmetic corrections are operations that solve problems of visible error and noise in the images. These can be line dropouts, line striping and random noise. While atmospheric corrections are done because atmospheric conditions have influence on the pixel values registered by the sensor. These corrections are related to the influence of haze, sun angle and skylight [18].

3.3.1 Striping

After importing the images a striping problem could be observed. To solve this problem, the ILWIS import option was used.

3.3.2 Haze correction

Haze problems increase the pixel values and decrease the overall contrast in the image. In infrared bands, water bodies have a brightness equal or near to zero because clear water bodies absorb strongly in the near infrared part of the spectrum and because very little infrared energy is scattered to the sensor from shadowed pixels [5]. This situation is used to reduce the effect of the haze on the satellite images. A black body, like a water body, is selected from the infrared band (band 3). It is supposed to have a zero DN value. The actual DN value is subtracted from all DN values of this band and the others bands.

3.3.3 Sun angle correction

The solar illumination changes depending on the hour of the day and the season of the year. For that reason the solar illumination is different for each image. It is very important to do the sun angle corrections when we are working with mosaics and multi-temporal data sets. A relative sun angle correction is applied in that case. The image with higher sun elevation angle is taken as a reference and the DN values of the other images are adjusted to it. In our multi-temporal

<table>
<thead>
<tr>
<th>Num.</th>
<th>Identification</th>
<th>Date</th>
<th>Lat</th>
<th>Long</th>
<th>Elev.</th>
<th>Angle</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>003_09082001111822.hdf</td>
<td>03–Jan–01</td>
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</tr>
<tr>
<td>2</td>
<td>003_10152001233337.hdf</td>
<td>02–Oct–01</td>
<td>−0.53</td>
<td>−78.36</td>
<td>71.20</td>
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</tr>
<tr>
<td>3</td>
<td>003_10292001133458.hdf</td>
<td>18–Oct–01</td>
<td>−0.55</td>
<td>−78.46</td>
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<tr>
<td>4</td>
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<tr>
<td>5</td>
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<td>−78.08</td>
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<tr>
<td>6</td>
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</tr>
<tr>
<td>7</td>
<td>003_06052003134530.hdf</td>
<td>17–May–03</td>
<td>−0.49</td>
<td>−78.08</td>
<td>62.06</td>
<td></td>
</tr>
</tbody>
</table>
images, the higher elevation angle corresponds to the image of October 2001. Its value is 71.2052. Then this value was applied to all images of the time series using the equation 3.1

\[ DN' = \frac{DN}{\sin \alpha} \]  

(3.1)

Where \( DN' \) is the output pixel value, \( DN \) is the input pixel value and \( \alpha \) is the sun elevation angle.

### 3.4 Geometric Corrections

At this point of our research it is not necessary that the multi-temporal images have geographic coordinates. For that reason we registered the images taking into account the master image. Image of January 2001 was selected as master image. All the other images were registered using image to image registration. Polynomial first order geometric model was used. Table 3.2 shows the RMSE for registration process.

**Table 3.2: RMSE’s for registration process.**

<table>
<thead>
<tr>
<th>Image</th>
<th>x</th>
<th>y</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1822.img</td>
<td>0.0151</td>
<td>0.0093</td>
<td>0.0177</td>
</tr>
<tr>
<td>2041.img</td>
<td>0.1622</td>
<td>0.0180</td>
<td>0.1632</td>
</tr>
<tr>
<td>3337.img</td>
<td>0.2904</td>
<td>0.00854</td>
<td>0.3027</td>
</tr>
<tr>
<td>3458.img</td>
<td>0.2488</td>
<td>0.2600</td>
<td>0.3599</td>
</tr>
<tr>
<td>4530.img</td>
<td>0.3048</td>
<td>0.1333</td>
<td>0.3326</td>
</tr>
<tr>
<td>5900.img</td>
<td>0.0038</td>
<td>0.2391</td>
<td>0.2392</td>
</tr>
<tr>
<td>2007.img</td>
<td>0.3477</td>
<td>0.0224</td>
<td>0.3485</td>
</tr>
</tbody>
</table>

#### 3.4.1 Multi-temporal images

Once that the images were registered it was possible to select the same area in all images. Then a subset was selected. The subset has 512 x 512 pixels. Finally the data set is composed by seven images. Figures 3.1 to 3.3 show the seven subset images selected and already corrected for haze and sun angle.

### 3.5 Cloud Detection

Cloud detection 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 (0.7mµ – 1.0cm) region of the electromagnetic spectrum.

The study 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. Meteosat and NOAA AVHRR satellites use hourly visible and thermal infrared images to assist in producing daily
3.5. Cloud Detection

Ice has a high reflectance in the visible range of the electromagnetic spectrum and water bodies have a low reflectance in the visible range. Spectral response of ice and water bodies is very similar to spectral response of clouds and their shadows.
3.5.1 Study cases

Nowadays there exist many approaches to detect clouds and their shadows in remote sensing images. We will discuss some of them.

One of them was developed using NOAA AVHRR time series image over the Far East Region, specifically in Korean peninsula. In this cloud detection method, a simple NDVI test was used to roughly separate land from ocean. After the NDVI test two test were carried out: a visible \((\text{channel}1 : 0.58\mu m - 0.68\mu m)\) or near-infrared \((\text{channel}2 : 0.725\mu m - 1.10\mu m)\) test and a thermal infrared test \((\text{Channel}4 : 10.3\mu m - 11.3\mu m)\). The visible and near-infrared test are very useful in detecting low clouds. The thermal infrared test aims to detect low temperature pixel corresponding to medium and high clouds. Results obtained with this method compared favourably with those obtained with the Saunders and Kriebel algorithm, which is a standard cloud detection procedure\[^{17}\].

Another study applied radiometric enhancements in order to detect clouds in satellite images. Contrast enhancement and spatial processing are actions to take into account regarding this topic. Contrast enhancement methods are:

- Thresholding, which produces a binary mask useful for identifying clouds in an optical image or water/land areas in SAR.
- Density slicing, which is used to display areas containing a certain range of values.
- Histogram stretching, for representation of the information content of almost all image data.

Cloud detection was applied using density slicing in the optical remote sensing data. Clouds and their shadows can be detected according to their DN value (approx 255 for clouds and approx 0 for shadows). Their borders have a different value. Density slicing was applied to the two visible bands (green and red) and to the one band of near infrared of SPOT XS because if it is applied only in one band then it would be affect other pixel values with similar grey value apart from clouds and shadows. Also a clump filter eliminates very small patches, which exist in the mask but do not represent clouds and shadows\[^{26}\].

A study compares the two classification algorithms, the fuzzy technique and an augmented form of the Iterative Self-Organizing Data Analysis (ISODATA) technique, which were used to discriminate low-altitude clouds and their shadows on a Landsat Thematic Mapper (TM) image of the Econlockhatchee River basin in central Florida-USA. After an unsupervised maximum-likelihood classification clouded and build-up pixels were mixed and shadows were mixed with water bodies. These regions were masked, then fuzzy and ISODATA classifications were performed on them. The ISODATA classification algorithm was run on the TM visible/short-wave bands and augmented with scatter diagrams of surface temperature versus several vegetation indexes. The fuzzy algorithm was applied in TM bands 1 through 5 and band 7. Fuzzy classification allows
multiple and partial membership for each pixel. It is more applicable to detect clouds and shadows than hard classification. The overall accuracy assessment of the augmented-ISODATA clustering was over 85 percent. The overall accuracy assessment of the fuzzy classification was 82 percent. This accuracy is very similar but the fuzzy technique did not require the added complexity of using temperature and vegetation index scatter diagrams[21].

As we saw in the previous approach for detecting clouds and their shadows on satellite imagery, all of them are using the visible and near infrared bands. The first approach also uses thermal infrared in order detect medium and high clouds. The second approach only uses the three visible and near infrared bands. The last approach uses the visible, near infrared and short infrared but also the thermal infrared in order to detect temperature index.

3.6 Wavelet Image Fusion

Image fusion using wavelet transformation only has been tackled over the last years and it has become an interesting alternative in the remote sensing field.

A method for fusion was proposed by Garzelli [13]. His method provides an integrated map of an urban area starting from co-registered optical (panchromatic and multispectral) and SAR images. This method selects specific information related to buildings from SAR data to be injected into the optical data. Another study, [25], suggest a method to fuse Landsat TM and IRS–1C images. Haar and Daubechies wavelet families were applied.

A Pixel–level fusion was proposed by Rockinger [33]. This method incorporates a shift invariant extension of the discrete Wavelet Transformation, based on the concept of the Wavelet Frames (WF).

Wavelet images fusion between hyperspectral and multispectral images was used by Gomes et al. [15]. Using the wavelet concept of hyperspectral and multispectral data fusion, this study performed image fusion between two spectral levels of a hyperspectral image and one band of a multispectral image. The new fused image has the same spectral resolution as the hyperspectral image and the same spatial resolution as the multispectral image with minimum artifacts.

Discrete wavelet transformation (DWT) and wavelet packages (WP) were used to fuse multitemporal city images of the same sensor. In wavelet package analysis, the details as well as the approximations 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 parts [16].

A new approach to fused images was explained by Shi [34]. First, a multi–band wavelet–based image fusion approach is presented. It is a two–band wavelet transformation. Secondly, a three–band (multi–band) wavelet transfor-
mation was applied. Finally an IHS image fusion approach was performed. The previous results were compared by means of quality indicators for assessing image fusion. Conclusions showed that image fusion using multi–band wavelet transformation performed better than two-band wavelet and IHS approaches.

A scheme to remove clouds and their shadows from a Landsat TM image was proposed by Wang et al. [40]. 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 (DWF) was adopted in this approach and it shows good fusion results even if there is misregistration between the two coregistered images. Only one–level wavelet decomposition is performed, because it is sufficient for this procedure.

Another approach of image fusion to fill out clouded areas was applied by Wisetphanichkij et al. [42]. Multi-spectral image (R,G,B) will be transformed to IHS (Intensity, Hue, Saturation) in order to make histogram matching. Next, wavelet decomposition was applied. The higher order coefficients were combined with the clouded image to compensate the hidden area.

An approach comparing different wavelet decomposition methods for fusing a high-resolution panchromatic image and a low resolution multispectral image is explained in Hong Wang et al. [41]. Results of Non-separable wavelet frame (NWF) performed better than IHS transform, Discrete wavelet transformation (DWT) and Discrete wavelet frame (DWF). The advantages of NWF are a better frequency characteristic, directional property and more degree of freedom. Drawback of NWF is that it needs more memory space and computation time than others.

Image fusion carried out using the Haar wavelet family showed to be efficient with results that are similar to those obtained with other wavelet families [20].

Two ways of wavelet image fusion can be done for fused panchromatic and multispectral images: substitution and addition method [23]. 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 IHS and LHS (Lightness-Hue-Saturation) methods.
3.6. Wavelet Image Fusion
Chapter 4

Implementation

This chapter explains detection of clouds and their shadows in remote sensing images using the wavelet approach.

As we saw in Section 3.5.1, there exist many methodologies for detection of clouds and their shadows. But only in the last years wavelet approaches have been used in remote sensing. We will explore three different methods for detection of clouds and their shadows using wavelet approaches and also an additional method for detection without using wavelets. After that we will compare all methodologies.

4.1 Pattern Recognition

The following procedure is based on a multiresolution approach for the inspection of local defect embedded in textured surfaces. Defects in a variety of real textures including machined surfaces, natural wood, sandpaper and textile fabrics were well detected [37]. In this research we discuss about the advantages of this approach in remote sensing images and for our specific task, cloud detection, we take in account clouds as discontinuities embedded in textured surface.

4.1.1 Wavelet decomposition

Let \( f(x, y) \) be the input image of size \( M \times N \). \( f(x, y) \) also can be represented by \( f_{LL}^{(0)}(x, y) \).

At first level decomposition it is possible to obtain one smooth sub-image \( f_{LL}(x', y') \), and three detail sub-images \( f_{LH}(x', y'), f_{HL}(x', y'), f_{HH}(x', y') \) that represent horizontal, vertical and diagonal details respectively.

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

On the other hand, wavelet synthesis is done by inverse wavelet transformation. \( W^{-1}[f^{(j)}] \) denotes the iteration of wavelet inverse transform of a sub-image \( f^{(j)} \) from resolution level \( j \) to level 0. For instance, \( W^{-1}[f_{LL}^{(3)}] \) is the reconstruction of smooth sub-image at resolution level 3.

For statistical textures with isotropic patterns the main energy is concentrated on the low frequency bands. For that reason only the smooth image needs to be included in the reconstruction process. For structural textures with high directionality the detail sub-images that correspond to the line direction in the original image is taken into account. If there are more than one line directions then reconstruction process takes into account more than one sub-images. In that case only the selective detail sub-images are included in the reconstruction process [37]. In this research we are dealing with satellite images without a clear structural texture. Those satellite images are taken into account as statistical texture with non-oriented patterns.

4.1.2 Energy of the wavelets

After one level decomposition it is possible to obtain one smooth sub-image and three detail images for horizontal, vertical and diagonal orientations. A reconstruction process taking into account smooth image or a combination of detail images at different resolution levels, allows us to remove repetitive patterns while preserving local anomalies.

The criteria to choose the number of decomposition levels and the appropriate sub-images for the reconstruction process is given by the energy distributions of the wavelet coefficients.

Wavelet energy is the normalized sum of square of detailed wavelet transform 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 image:

\[
E^J_S = \sum_x \sum_y [f_{LL}^{(j)}(x, y)]^2
\]  

(4.1)

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

\[
E^J_h = \sum_x \sum_y [f_{LH}^{(j)}(x, y)]^2, \quad j = 1, 2, \ldots, J
\]  

(4.2)

Energy of the vertical detail sub-image at level \( j \):

\[
E^J_v = \sum_x \sum_y [f_{HL}^{(j)}(x, y)]^2, \quad j = 1, 2, \ldots, J
\]  

(4.3)

Energy of the diagonal detail sub-image at level \( j \):

\[
E^J_d = \sum_x \sum_y [f_{HH}^{(j)}(x, y)]^2, \quad j = 1, 2, \ldots, J
\]  

(4.4)
The total energy of the image \( f(x, y) \) in \( J \) multi-resolution levels is given by

\[
E = E_J^S + \sum_{j=1}^{J} E_h^j + \sum_{j=J}^{J} E_v^j + \sum_{j=J}^{J} E_d^j
\]  

(4.5)

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

Normalized energy of smooth image

\[
E_S = \frac{E_J^S}{E}
\]  

(4.6)

Normalized energy of horizontal detail sub-image.

\[
E_H = \frac{1}{E} \sum_{j=1}^{J} E_h^j
\]  

(4.7)

Normalized energy of vertical detail sub-image.

\[
E_V = \frac{1}{E} \sum_{j=1}^{J} E_v^j
\]  

(4.8)

Normalized energy of diagonal detail sub-image.

\[
E_D = \frac{1}{E} \sum_{j=1}^{J} E_d^j
\]  

(4.9)

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

\[
E_S + E_H + E_V + E_D = 1
\]  

(4.10)

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 concentrate 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 \( T_S \).

\[
\hat{f}(x, y) = W^{-1}[f_{LL}^{(j)}] \quad \text{if} \quad E_S > T_S
\]  

(4.11)

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 or/and diagonal) and emphasize the local animalities. In cases of an image containing an oriented pattern in horizontal, vertical and diagonal directions, the three normalized energies \( E_H, E_V \) and \( E_D \) will have similar values. In
4.1. Pattern Recognition

In this case the smooth image is selected for reconstruction. When \( E_S < T_S \) it is necessary to define another threshold \( T_D \):

\[
\hat{f}_H(x,y) = \begin{cases} 
W^{-1}[f_{1LH}^{(1)}} \  & \text{if } \frac{E_H}{T_{max}} < T_D \\
0, \quad & \text{otherwise}
\end{cases}
\]

\[
\hat{f}_V(x,y) = \begin{cases} 
W^{-1}[f_{1HL}^{(1)}} \  & \text{if } \frac{E_V}{T_{max}} < T_D \\
0, \quad & \text{otherwise}
\end{cases}
\]

\[
\hat{f}_D(x,y) = \begin{cases} 
W^{-1}[f_{1HH}^{(1)}} \  & \text{if } \frac{E_D}{T_{max}} < T_D \\
0, \quad & \text{otherwise}
\end{cases}
\]

\( T_D \) threshold is chosen to detect the significance of directionality in detail sub-images. In this research, threshold values \( T_S \) 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. As a reference we can use the energy corresponding to the average of the smooth energies. For setting the \( T_D \) threshold we take in account that the energy of the detail sub-image must represent at least one third of the highest energy values. That is because the detail sub-image that contains no directional information of the original image has distinctly small energy value.

Figure 4.1 shows a flow chart of the sub-image selection procedure for image reconstruction.

**Multi-resolution levels**

As we mentioned in Section 4.1.2, decomposition of a textured image in its proper resolution will effectively eliminate repetitive patterns and highlight the local anomalies. For structural textures with high directionality, the oriented patterns in horizontal, vertical and diagonal directions are well separated in the first decomposition level (\( J=1 \)). For statistical textures with isotropic patterns or structural textures containing all horizontal, vertical and diagonal orientations, the smooth sub-image is used for reconstruction. Increasing the number of resolution levels leads to increasing uniformity of grey levels in the restore image. However, when the number of multi-resolution levels becomes too large it will generate a fusion effect for the anomalies, and may cause localization errors [37].

The choice of a proper decomposition level is based on the energy ratio of detail sub-images on two consecutive levels.

\[
D_j = \frac{(E_h^j + E_v^j + E_d^j)}{E} \tag{4.12}
\]

Let \( R_j \) to be the energy ratio of detail sub-images between resolution levels \( j \) and \( j-1 \).
Figure 4.1: Image reconstruction flow chart

\[ R_j = \frac{D_j}{D_{j-1}}, \quad j = 1, 2, \ldots, J_{\text{max}} \]  

(4.13)

Generally, the maximum number of resolution levels \( J_{\text{max}} \) is no more than six. The best number of resolution levels \( J^* \) is chosen such that \( R_{j^*} \) is a minimum,

\[ J^* = \arg \{ \min_j \{ R_j \} \} \]  

(4.14)

The minimum value of \( R_j \) represents that the high frequency components between two consecutive multi-resolution levels are sufficiently separated in terms of marginal improvement, and the decomposition process should be stopped. For multi-resolution level \( j < J^* \), \( R_j \) indicates that some detail (high frequency) components still remain in the coarse approximation, and the smooth image should be further decomposed. For multi-resolution level \( j > J^* \), \( R_j \) indicates that the high frequency components are over smoothed [37].
4.2 Stationary wavelets approach

Wang [40] proposed automated cloud detection in a set of two temporal Landsat TM images by simply thresholding high frequency components as extracted by a 2D discrete wavelet transform of both images. That study suggests an automated use of Discrete Wavelet Frames (DWF) in order to detect clouds and their shadows in satellite images. The special frame mentioned in his paper can be called undecimated wavelet transform or stationary wavelet transform (SWT).

Compared with the orthogonal wavelet transform with Mallat algorithm, the wavelet coefficients from the wavelet frame are translation-invariant. For the image texture, you may acquire the same image with a sample shift. If you apply the traditional wavelet transform, the wavelet coefficients will change. But for the wavelet frame, there is only 1 sample shift in the coefficients. Such property is very suitable in signal/image feature extraction although the redundancy from the frame is harmful for signal/image compression. This property is very useful for several applications such as breakdown points detection.

The drawback of the DWT is that it is not a time-invariant transform. This means that, even with periodical signal extension, the DWT of a translated version of a signal $X$ is not, in general, the translated version of the DWT of $X$. The idea is to average some slightly different DWT, called $\varepsilon$-decimated DWT, to define the stationary wavelet transform (SWT)[22].

The DWF or SWT are similar to a discrete wavelet transformation (DWT). The difference between both of them is that DWF does not perform downsampling of the signal between the levels of hierarchy. For that reason the sub-images obtained after the decomposition process have the same resolution as the original image.

This procedure used details images and it is explained in Figure 4.3.

4.3 Multi-scale product using SWT

The two previous approaches have been focused on detecting clouds and their shadows only one decomposition level. This approach performs a detection of clouds and their shadows using two wavelet decomposition levels.

Carvalho [8] mentioned that clouds and their shadows appear as peaks of narrow bandwidth in the temporal spectrum (time series). In the spatial domain they appear in a similar way but with variable bandwidth. If we consider the presence of clouds and their shadows as signal response against a "noisy" background, a framework for their detection can be set forth based on noise modelling in transformed space.
Figure 4.2: Clouds detection process using SWT

Figure 4.3 shows the multi-scale product process using SWT. First of all a wavelet decomposition is achieved at two decomposition levels. Details images are added for each decomposition level. As a result we obtained two added images, one for each decomposition level. After that, multi-scale product is joined with the previous decomposed images.

Multi-scale point-wise product was applied in order to further enhance singularities (i.e., edges and peaks) in the signal. That inter-scale correlation is represented by equation 4.15.

\[ p(t) = \prod_{j \in K} d_j(t) \quad (4.15) \]

Using an even number of scales in the product, positive and negative singularities in wavelet domain are represented only as positive singularities in the multi-scale product space facilitating the detection procedure.

A threshold was applied in order to detect clouds. As a result clouds were detected but also many isolated pixels. A majority filter was applied and isolated pixels were removed.
4.4 No wavelet approach

This approach to detect clouds and their shadows allows us to compare with the three previous wavelet approaches in order to know the accuracy of each methodology. The procedure is showed in Figure 4.4.

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 area 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.

4.4.1 Brightness correction

A linear relation was considered in order to reduce the different solar irradiance and atmospheric effects on the brightness value of the two or more images. The main image is considered as standard and the reference image is adjusted.

$$f'_{\text{ref}}(i,j) = \frac{\sigma_{\text{main}}}{\sigma_{\text{ref}}} [f_{\text{ref}}(i,j) - m_{\text{ref}}] + m_{\text{main}}$$  \hspace{1cm} (4.16)

where $f_{\text{ref}}(i,j)$ is the previous brightness value of a pixel of the reference
image, $f'_{\text{ref}}(i,j)$ is the new brightness value of the reference image. $m_{\text{ref}}$ and $m_{\text{main}}$ are the main of the reference image and the main of the main images respectively. $\sigma_{\text{ref}}$ and $\sigma_{\text{main}}$ are the standard deviation of the reference image and the standard deviation of the main image respectively [40].

### 4.4.2 Detection of Clouds and their shadows

Using the two previously corrected images, we set a threshold $C_1$ to differentiate the clouded regions and the shadowed regions in the images. It is important to take into account that clouds reflect the solar radiation higher than the ground in the visible and infrared bands. On the contrary, shadow areas do not get directly solar radiation, for that reason we always obtain very low DN values.

Consider only the previous threshold is not a guarantee for a correct detection of clouds and shadows. Many features on the ground have similar DN value as clouds (i.e, building areas, greenhouses, bare soil) and also other features show a reflection very similar to that of shadows (i.e, water bodies, topographic shadows). But those object does not have a unique property that
4.5 Filling out gaps using wavelet image fusion

clouds and shadows have. That is movement. This is way, in addition to the previous threshold \( C_1 \) we need to define another threshold, this time \( C_2 \). To be sure about a correct detection, the absolute brightness difference between the same locations of the main image and the brightness-corrected reference image is compared with threshold \( C_2 \). Equation 4.17 shows this procedure for clouds and shadows detection.

\[
\left( (f_{main}(i,j) > C_1) \cup (f'_{ref}(i,j) > C_1) \right) \cap \left( |f_{main}(i,j) - f'_{ref}(i,j)| > C_2 \right)
\] (4.17)

4.5 Filling out gaps using wavelet image fusion

In Section 3.6 of this thesis some different approaches to image fusion were explained. Most of them perform image fusion using the wavelet domain of images from different sensors. Wavelets have been used to fuse high-resolution panchromatic images and low resolution multispectral images. Those approaches have showed better results than more traditional methods. Also, fusion process for images of the same spatial and spectral characteristics have been done in previous studies. Those information correspond to different dates (multitemporal data).

Image fusion using Haar wavelet family showed efficient results. Those results are similar using other wavelet families [20]. Other study showed that the influence of the wavelet family used in the analysis and synthesis process is nearly neglect. It is possible to have stable fusion results using different wavelet families (Haar, Daubechies–2, Daubechies symmetric, Spline (2,2) and (4,4))[33].

Taking in account the number of wavelet decomposition levels, only one–level wavelet decomposition it is sufficient because it has good results for image fusion procedure [40].

Different wavelet transformation methods have been applied. Image fusion have been produced using Wavelet Packages (WP) [16], Discrete wavelet frames (DWF) [33], [40], [41] and multi–band transformation [34]. Non-separable wavelet frame (NWF) performed better than Discrete wavelet frame (DWF). All of them perform better than the Discrete wavelet transformation (DWT).

In this research it was applied Stationary wavelet transformation (SWT) as a synonymous alternative for DWF. In Section 4.2 the relationship between them is explained.

In order to fill out the missing information caused by clouds and their shadows in the ASTER images of this research, image fusion using wavelet approach was applied, as show in Figure 4.5.

For this process, two co–registered images are selected. In this case, we selected a cloud–free image as main image and a clouded image selected as ref-
Chapter 4. Implementation

Figure 4.5: Pixel-based wavelet image fusion

Stationary wavelet transformation at level one 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 level stationary wavelet transformation (LL, LH, HL and HH) were used for the combined transform process.
4.5. Filling out gaps using wavelet image fusion
Chapter 5

Results and Discussion

In this research, implementation process was tackled using different softwares. Wavelet decomposition and reconstruction process were performed using MATLAB 6.5.1. Also matrix operations were performed using that software. On the other hand, images processing was performed using ERDAS Imagine 8.6 and ILWIS 3.12.

In this chapter we describe the results obtained after application of four different methodologies explained in the previous chapter in order to detect clouds and their shadows. Three approaches apply wavelet domain and one does not apply wavelet approach.

First of all, we analyse the results obtained using the pattern recognition approach. After that a stationary wavelet (SWT) approach is used as an alternative to Discrete wavelet transform (DWT). Next, a multi-scale product using Stationary wavelet approach is applied to explore the advantage of working with multi-scale information. After, a no wavelet approach was used to detect clouds and their shadows. All clouds detection approaches were assessed using an Error Matrix.

Finally, filling out missing information using wavelet image fusion was performed and also the evaluation of the fusion process was considered.

5.1 Pattern Recognition

This section describes the results obtained after the implementation of the Pattern Recognition methodology explained in section 4.1.

First of all, it was necessary to select a band of the ASTER satellite image in order to apply the wavelet transformation. The criteria used selected the band having the high grey values representing clouds. Also the band where there was the higher grey value representing shadows relative to other bands. We are interesting to use the visible bands in order to preserve the high spatial resolution of ASTER images. Figure 5.1 shows, the high gray values correspond to band 1.
Wavelet decomposition was applied to image 2007. Haar family wavelet was used at five decomposition levels. Figure 5.2 shows the discrete wavelet decomposition process.

Applying equations 4.1, 4.2, 4.3, 4.4, 4.5 the energy of the smooth image
and three detail images (horizontal, vertical and diagonal) and the total energy of the image were computed for five decomposition levels. Table 5.1 shows the results.

<table>
<thead>
<tr>
<th>Level</th>
<th>$E_s$</th>
<th>$E_h$</th>
<th>$E_d$</th>
<th>$E_v$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4,473,570,761</td>
<td>20,793,232</td>
<td>20,471,791</td>
<td>4,842,670</td>
</tr>
<tr>
<td>2</td>
<td>4,405,494,782</td>
<td>32,241,719</td>
<td>26,453,957</td>
<td>9,380,303</td>
</tr>
<tr>
<td>3</td>
<td>432,152,5392</td>
<td>40,746,592</td>
<td>29,836,511</td>
<td>13,386,288</td>
</tr>
<tr>
<td>4</td>
<td>423,873,5379</td>
<td>39,542,912</td>
<td>28,082,872</td>
<td>15,164,229</td>
</tr>
<tr>
<td>5</td>
<td>415,748,2023</td>
<td>38,755,105</td>
<td>26,493,460</td>
<td>16,004,791</td>
</tr>
<tr>
<td>Total</td>
<td>172,079,560</td>
<td>131,338,590</td>
<td>58,778,280</td>
<td></td>
</tr>
<tr>
<td>Total energy</td>
<td>4,519,678,453</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The normalized energy for the smooth image and horizontal, vertical and diagonal details were computed at five resolution levels. Equations 4.6, 4.7, 4.8, 4.9 were used. Table 5.2 shows the results and also the total normalized energy equal to 1.

<table>
<thead>
<tr>
<th>Level</th>
<th>$E_s$</th>
<th>$E_h$</th>
<th>$E_d$</th>
<th>$E_v$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.990</td>
<td>0.00460</td>
<td>0.00453</td>
<td>0.00107</td>
</tr>
<tr>
<td>2</td>
<td>0.975</td>
<td>0.00713</td>
<td>0.00585</td>
<td>0.00208</td>
</tr>
<tr>
<td>3</td>
<td>0.956</td>
<td>0.00902</td>
<td>0.00660</td>
<td>0.00296</td>
</tr>
<tr>
<td>4</td>
<td>0.938</td>
<td>0.00875</td>
<td>0.00621</td>
<td>0.00336</td>
</tr>
<tr>
<td>5</td>
<td>0.920</td>
<td>0.00857</td>
<td>0.00586</td>
<td>0.00354</td>
</tr>
<tr>
<td>Total</td>
<td>0.03807</td>
<td>0.02906</td>
<td>0.01300</td>
<td></td>
</tr>
<tr>
<td>Total energy</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Also, table 5.3 shows the energy ratios $R_j$ at five decomposition level.

<table>
<thead>
<tr>
<th>Level</th>
<th>$E_s$</th>
<th>$D_j$</th>
<th>$R_j$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.990</td>
<td>0.010</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.975</td>
<td>0.015</td>
<td>1.48</td>
</tr>
<tr>
<td>3</td>
<td>0.956</td>
<td>0.019</td>
<td>1.23</td>
</tr>
<tr>
<td>4</td>
<td>0.938</td>
<td>0.018</td>
<td>0.99</td>
</tr>
<tr>
<td>5</td>
<td>0.920</td>
<td>0.018</td>
<td>0.98</td>
</tr>
</tbody>
</table>

In this research, the threshold values of $T_S$ and $T_D$ are setting at 0.95 and
0.33, respectively, at the third multi-resolution level \((J = 3)\). We described this selection process in Subsection 4.1.2.

Figure 4.1 describes the flow chart of the sub-image selection procedure for image reconstruction. Applying it to the results obtained for wavelet energies we observed that the normalized energy of smooth sub-image \(E_S\) at level 3 is greater than the threshold \(T_S\). For that reason we should restore the smooth sub-image. The resolution level selected should be five because we can see in Table 5.3 that the minimum \(R_j\) value occurs at level five. Figure 5.2 shows (at upper-right) the reconstruction of approximation coefficients at level 5. As we can see this level of decomposition is very coarse and it is not possible to differentiate clouds and their shadows. On the other hand, if we see in Figure 5.2 all the decomposed sub-images at five levels (lower-right) we can observe that clouds are well detected at level 1 and also at level 2.

As aforementioned in 4.1.2 (sub-section Multi-resolution levels), for structural textures with high directionality, the oriented pattern in horizontal, vertical and diagonal directions are well separated in the first decomposition level \((J = 1)\). Then we assume that the satellite image has oriented patterns in horizontal, vertical and diagonal directions. Then we can use the smooth sub-image at first decomposition level for the reconstruction process. In order to create a mask of clouds and their shadows, we selected a threshold to differentiate clouds and their shadows and after that we applied a majority filter. We obtained the results showed in Figure 5.3

![Figure 5.3: Pattern Recognition. (left): Original Image (right): Clouds and shadows detection](image)

As we can see in the results, clouds and their shadows are well detected but also cities, bare soil and green-houses are detected as clouds. Topographic shadows are detected as shadows produced by clouds.
We assume that the mis-detection of other features as clouds and shadows occurs because our study area is a very irregular and complex area. There are hardly any defined patterns and the spectral responses of different features on the ground have almost similar values as clouds and shadows. On the other hand, if we apply the previous methodology to detect clouds and their shadows in an area with more regular patterns like deserts, forest or grass-land, this methodology would be very useful to detect clouds and their shadows. In this case, our study area is very heterogeneity with many features with the same DN value as clouds and shadows. Working with images having structural textures with oriented patterns and statistical textures with isotropic directionality are the optimal field to apply this methodology.

Also it is important to observe that decomposition at level 1 is enough for cloud detection.

### 5.2 Stationary wavelets approach

In order to detect clouds using SWT first the original image was decomposed at one level resolution decomposition using SWT. As a result we obtained one smooth image and three detail images (horizontal, vertical and diagonal). All those images have the same resolution as the original image. The three detail images were smoothed by a 3 x 3 low pass filter. Then smoothed images were added and applying a threshold to differentiate clouds a new binary image was obtained. In the previous process some isolated pixels were detected as cloud for that reason it was necessary to apply a majority filter to eliminate the miss detected pixels. Figure 4.2 shows a diagram of the process above.

After applying the process explained in section 4.2 to detect clouds we obtained the results showed in Figures 5.4 to 5.6.

Figure 5.4 (left) shows the original image before SWT. Figures 5.4 (right), 5.5 (left) and 5.5 (right) show the horizontal, vertical and diagonal detail sub-images after applying the low pass filter. The three previous images were added, Figure 5.6 (left) and finally a threshold was applied and a majority filter to eliminate the isolate detected pixels. Figure 5.6 (right) shows the final clouds detection using SWT approach.

As we can see in the results, clouds detection is achieved. But for shadow detection the previous procedure did not work. It is possible to detect some shadows but at the same time other features are detected as shadows.

### 5.3 Multi-scale product using SWT

Applying the procedure explained in Section 4.3, it was possible to obtain the following results.
5.3. Multi-scale product using SWT

Figure 5.4: SWT. (left): Original Image (right): Horizontal details

Figure 5.5: SWT. (left): Vertical Details (right): Diagonal details

Figure 5.7 (left) shows the original image before wavelet transformation. Figures 5.7 (right) and 5.8 (left) show the result after adding images for level 1 and 2, respectively. As we can see level 2 images have a coarse resolution. Figure 5.8 (right) shows the resulting image after the multi-level product and finally Figure 5.9 shows the clouds detection results after applying a threshold and a majority filter.

The cloud detection approach detects clouds in a good way but in addition mistakes some features as bare soil and greenhouses for clouds. Shadow detection using this approach did not give good results because many other features are also detected as shadows.
5.4 No wavelet approach

Following the procedure described in Figure 4.4 we obtained the following results.

First of all 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 (2007) as a reference image and the other one is an image without clouds and shadows (1822) as a main image.

The selection criteria to choose the main image was the fact that image 1822 does not have clouds. That allows us to detect only clouds and their shadows of
the reference images. We had good results in the detection process of the reference image. Figure 5.10 (left) and 5.10 (right) show us the main image and the referenced image respectively. Figure 5.11 (left) shows the clouds detection results and 5.11 (right) shows the cloud detection results.

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.
Figures 5.12 (left) and 5.12 (right) show us the main and reference image respectively. Brightness correction of reference image was applied taking as reference the main image. Figure 5.13 (left) shows the clouds detection results. As we can see, clouds of two image are detected in only one image mask. And shadows are also represented in the same way as show figure 5.13 (right).

5.5 Accuracy Assessment

In order to evaluate previous results an Error Matrix was constructed for each approach. We selected 195 reference points in the original image. The distribu-
5.5. Accuracy Assessment

As we can see in Table 5.4, the better overall classification accuracy corresponds to the No wavelet approach (88%), followed by Multi-scale product approach (87%).

For detection of clouds, the overall accuracy is quite good but producer accuracy for No wavelet approach is only 52%, which means that of the clouded pixels in the original image, only 52% was correctly classified using this approach. On the other hand, Producer accuracy for clouds of Multiscale product is 100%. User accuracies for both approaches are good, which means that if the algorithm detects a cloud, there is indeed a cloud.
Regarding the approaches for the detection of shadows, No wavelet and Pattern recognition, show an accuracy of 86% and 79% respectively. Producer accuracies for those approaches are very low (46% and 38% respectively). Therefore, of the pixels representing shadows in the original image, only 46% and 38% were correctly classified using those approaches. User accuracy for both approaches is very good.

Also it is important to see that although the overall accuracy of Pattern recognition approach is only 79%, it has good producer accuracy and user accuracy, the classification error is distributed more equally than with the other approaches.

### 5.6 Filling out missing information

Following the procedure for wavelet image fusion explained in Section 4.5 we obtained the following results.

Figure 5.14 (right) shows a result of a fused process. All the four sub-images resulting of the first level stationary wavelet transformation (LL, LH, HL and HH) were used in the combined and reconstruction process. In other words, the approximation and also the details sub–images of the non–clouded image were replaced in the clouded image.

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 image were used in the reconstruction. In the second procedure, the detail sub–images of the
5.6. Filling out missing information

Clouded image were used in the reconstruction. Figure 5.15 shows the fusion results of those procedures.

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 it showed 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. Image fusion results depend on the quality of the detection of the clouds and their shadows.
5.6.1 Assessing Image fusion results

In this research, the 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. Figures 5.16 and 5.17 show a zoom of the right–lower part of the simple replacement and wavelet fusion results.

![Figure 5.16](image1)

Figure 5.16: (left): Simple replacement method (right): Combine approximations and details

![Figure 5.17](image2)

Figure 5.17: (left): Using details of clouded image (right): Using details of non-clouded image

In a visual inspection, we can see in the simple replacement method, Figure 5.16 (left) the replaced areas are very easy to identify (e.g. red squares). 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 Figure 5.16 (right) and
Figure 5.17 (left and right).

Also, in Figure 5.17 (left) we can see that there are some blurs in the replaced areas (e.g. green square). In Figure 5.16 (right) and Figure 5.17 (right) the results are much clearer.

For the visual inspection it can be concluded that image fusion results using wavelet approaches perform better than a simple replacement procedure. Furthermore, combining approximations and details of the two image in the fusion process and combining approximation and details of the non-clouded image are the best procedure to fill in the missing information in this research.

There are some quality assessment methods for image fusion. Three methods evaluate image quality, those are listed in Table 5.5.

<table>
<thead>
<tr>
<th>Method</th>
<th>Quality indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistics</td>
<td>Min, max, mean, median, mode, Sd.</td>
</tr>
<tr>
<td>Details</td>
<td>Variation</td>
</tr>
<tr>
<td></td>
<td>Information entropy</td>
</tr>
<tr>
<td></td>
<td>Directional entropy</td>
</tr>
<tr>
<td></td>
<td>Profile intensity curve</td>
</tr>
<tr>
<td>Spectrum</td>
<td>Bias</td>
</tr>
<tr>
<td></td>
<td>Correlation coefficients</td>
</tr>
<tr>
<td></td>
<td>Warping degree</td>
</tr>
</tbody>
</table>

During this research we used the statistics and correlation coefficients indicators. The statistic parameters between the original clouded image, wavelet fusion results and simple replacement results are shown in Table 5.6. Those parameters show that the histograms of the original image and all results are very similar.

The Correlation coefficient of the original image and the fused image is used to indicate the correlation between them. 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 [34]. The correlation coefficient is given by 5.1.

\[
Corr(A/B) = \frac{\sum_{j=1}^{n} \sum_{i=1}^{m} (x_{i,j} - \mu(A))(x'_{i,j} - \mu(B))}{\sqrt{\sum_{j=1}^{n} \sum_{i=1}^{m} (x_{i,j} - \mu(A))^2 \sum_{j=1}^{n} \sum_{i=1}^{m} (x'_{i,j} - \mu(B))^2}} \tag{5.1}
\]

Were, A and B are two images, \(x_{i,j}\) and \(x'_{i,j}\) are the element of image A and the image B respectively. \(\mu(A)\) and \(\mu(B)\) stand for their mean values.
Table 5.6: Statistic parameters of the original image, wavelet fusion results and simple replacement results

<table>
<thead>
<tr>
<th></th>
<th>Original Image</th>
<th>Combine details</th>
<th>non-clouded details</th>
<th>clouded details</th>
<th>Simple replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Max</td>
<td>255</td>
<td>255</td>
<td>255</td>
<td>255</td>
<td>255</td>
</tr>
<tr>
<td>Mean</td>
<td>123.3</td>
<td>120.8</td>
<td>120.8</td>
<td>120.8</td>
<td>121.3</td>
</tr>
<tr>
<td>Median</td>
<td>118</td>
<td>127.5</td>
<td>127.5</td>
<td>127.5</td>
<td>118.0</td>
</tr>
<tr>
<td>Mode</td>
<td>109</td>
<td>108.6</td>
<td>105.6</td>
<td>108.6</td>
<td>109.0</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>45.0</td>
<td>40.3</td>
<td>41.0</td>
<td>40.0</td>
<td>40.6</td>
</tr>
</tbody>
</table>

Table 5.7: Correlation coefficients between wavelet approaches and simple replacement approach

<table>
<thead>
<tr>
<th>Wavelet approaches</th>
<th>Correlation coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Using details of non-clouded image</td>
<td>0.94</td>
</tr>
<tr>
<td>Using details of clouded image</td>
<td>0.98</td>
</tr>
<tr>
<td>Using combined details</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Table 5.7 shows the correlations between wavelet approaches and the simple replacement procedure. As we can see, there is a strong correlation between them. The correlation coefficient of the wavelet approach combining approximations but also details is 0.99%. That means that the resulting image maintains the information of the source images (clouded and non-clouded images) but the result is a more smooth image as we saw in visual inspection. As a conclusion, we can say that the 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.
5.6. Filling out missing information
Chapter 6

Conclusions and Recommendations

6.1 Conclusions

The following conclusions can be drawn from this research:

1. The Pattern recognition approach detected the clouds correctly but also some other objects were detected as clouds. As well, shadow detection had the same behaviour. This approach could perform better in areas with more homogeneous textures and regular patterns.

2. The two approaches involving Stationary wavelet transformation (SWT), used details sub-images to detect clouds and their shadows. Clouds were detected but those approaches were not suitable for detection of shadows.

3. Using inter-scale correlation as applied in the Multi-scale Product approach, results in a good enhancement of singularities, such as clouds.

4. Wavelet approaches as used in this research did not perform better than the non-wavelet approach for detection of clouds and shadows.

5. In all cases bigger clouds were detected better than smaller clouds.

6. The results of the fusion step to fill in the missing information depend on the accurate detection of clouds and their shadows.

7. Wavelet approaches for fill out clouded areas performed better than simple replacement method.

8. The best approach in this research was done combining the approximation sub–images but also the detail sub–images in order to perform the wavelet reconstruction process.
6.2 Recommendations

Here we will list some potential research areas, which was not explored during this work or need more exploration.

1. Apply the Pattern recognition approach to detect clouds and shadows in a satellite images of areas with regular patterns like forests, grasslands or water.

2. Explore the potential of Stationary wavelet transform (SWT) using approximation sub-image for detection of shadows.

3. Experiment with detection of clouds and their shadows using other wavelet families. Probably using another wavelet family the pixels on the borders of clouds will be detected better.

4. Try this procedure in images with larger clouds. Maybe working with larger clouds it is possible to use more decomposition levels without smoothing the image to much.

5. Use more than two images in the image fusion process. In case that two images have clouds and shadows overlapping at the same location, an extra image could be used for fill in missing information.
Bibliography


[38] Monica Wachowicz and Luis Tavares de Carvalho. Data fusion ans mining for the automation of a space–time reasoning process. Centre for Geoinformation–Wageningen University.


