ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 2, August 2012

Enhanced Techniques for Edge Detection in SAR Images

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***Abstract:* This paper presents a novel technique for automatic edge enhancement and detection in synthetic aperture radar (SAR) images. The characteristics of SAR images justify the importance of an edge enhancement step prior to edge detection. Therefore, this paper presents a robust and unsupervised edge enhancement algorithm based on a combination of wavelet coefficients at different scales. The performance of the method is first tested on simulated images. This paper suggests the extraction of the coastline in SAR images as a particular case of edge detection. Hence, after highlighting its practical interest, the technique that is theoretically presented in the first part of this paper is applied to real scenarios.**

***Index Terms*—Edge Detection, Synthetic Aperture Radar (SAR), Wavelet Transform.**

I. INTRODUCTION

Image processing is a rapidly growing area of computer science. Its growth has been fueled by technological advances in digital imaging, computer processors and mass storage devices. Fields which traditionally used analog imaging are now switching to digital systems, for their flexibility and affordability. Important examples are medicine, film and video production, photography, remote sensing, and security monitoring. These and other sources produce huge volumes of digital image data every day, more than could ever be examined manually. Digital image processing is concerned primarily with extracting useful information from images. Ideally, this is done by computers, with little or no human intervention. Image processing algorithms may be placed at three levels. At the lowest level are those techniques which deal directly with the raw, possibly noisy pixel values, with denoising and edge detection being good examples. In the middle are algorithms which utilise low level results for further means, such as segmentation and edge linking. At the highest level are those methods which attempt to extract semantic meaning from the information provided by the lower levels, for example, handwriting recognition. In this work a novel technique for automatic edge enhancement and detection in synthetic aperture radar (SAR) images is proposed. However, there does not appear to be any unifying principle guiding many of them. Some are one dimensional signal processing techniques which have been extended to two dimensions. Others apply methods from alternative disciplines to image data in a somewhat inappropriate manner. Many are the same basic algorithm with parameter values tweaked to suit the problem at hand. Alternatively, the parameters are optimized with respect to a suitable training set, without thought on how to vary them for images with different properties. There do exist well considered methods, but unfortunately a large proportion of new ideas have been *ad hoc*, without any central guiding principle.

Fundamental Steps in Image Processing

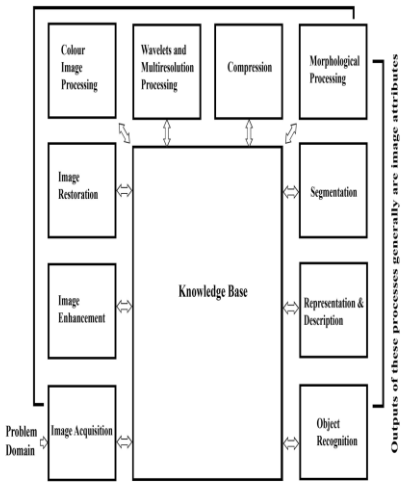

Fig 1. Fundamental Steps in Image Processing

1. ***Image Restoration***: Image restoration is based on mathematical and probabilistic models of image degradation.
2. ***Color Image Processing***: It has been gaining in importance because of the significant increase in the use of digital images
3. ***Wavelets***: These are the foundation for representing images in various degrees of resolution.
4. ***Compression:*** This deals with techniques for reducing the storage required saving an image or the bandwidth required transmitting it.
5. ***Morphological Processing***: This deals with tools for extracting image components that are useful in the representation and description of shape.
6. ***Segmentation***: Segmentation procedures partition an image into its constituent parts or objects
7. ***Representation and description***: This almost always follows the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region or all the points in the region itself.

Image Segmentation: The growing need for automated image analysis and interpretation in a wide range of applications necessitates the development of segmentation algorithms. Segmentation involves partitioning an image into a set of homogeneous and meaningful regions, such that the pixels in each partitioned region possess an identical set of properties or

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ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 2, August 2012

attributes. These sets of properties of the image may include gray levels, contrast, spectral values, or textural properties. The result of segmentation is a number of homogeneous regions, each having an unique label. An image is thus defined by a set of regions that are connected and no overlapping, the set of objects of interest in an image, which are segmented, undergoes subsequent processing, such as object classification and scene description. Segmentation refers to the process of partitioning a digital image into multiple segments The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture.

Basic Concepts of the Pixels:

Neighborhood: A pixel 'P' at coordinates (x,y) has four horizontal and vertical neighbors whose coordinates are given by **(x+1,y), (x-1,y), (x,y+1), (x,y-1).** This set of pixels called the 4-neighbors of P is denoted by N_4 (P).Each pixel is a unit distance from (x,y), and some of the neighbors of P lie outside the digital image if (x,y) is on the border of the image. The four diagonal neighbors of P have coordinates **(x+1,y+1), (x+1,y-1),(x-1,y+1), (x-1,y-1)** are denoted by N_8(P).

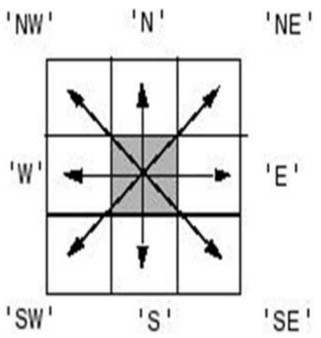

Fig .2. Neighborhood Representation

Connectivity: Connectivity between pixels is a fundamental concept that simplifies the definition of numerous digital image concepts, such as regions and boundaries. To establish if two pixels are connected, it must be determined if they are neighbors and if their gray levels are equal. For instance in a binary image with values 0 and 1, two pixels may be 4-neighbors, but they are said to be connected only if they have the same value. The Figure 3 shown above contains a set of pixels and the whole set is light grey color. In this set there is subset of pixels 'S' which has dark grey color. In this subset consider two pixels p and q, these two are said to be connected in S if there exists a path between them consisting entirely of pixels in S. For any pixel p in S, the set of pixels that are connected to it in S is called a **'connected component'** of S.

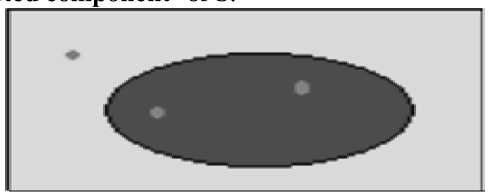

Fig .3.Connectivity

Outside the subset there is another pixel. This pixel is not connected with any of the subset pixels as their intensity levels are different.

Adjacency: Consider a set of gray-level values to define the adjacency. In a binary image, V= {1} indicates that we are referring to adjacency of pixels with value 1. In gray scale image V typically contains more elements. The range is from 0 to 255. Generally we use two types of adjacencies. They are 4-adjacency: Two pixels p and q with values from V are 4-adjacent if q is in the set N_4(P). 8-adjacency: Two pixels p and q with values from V are 8-adjacent if q is in the set N_8(P).

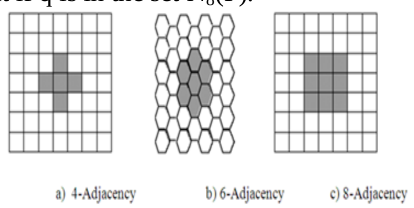

Fig .4 Adjacency

Boundary: Let R be a subset of pixels in an image. We call R a region of the image if R is a connected set. The boundary of a region R is the set of pixels in the region that have one or more neighbors that are not in R. if R happens to be an entire image then its boundary is defined as the set of pixels in the first and last rows and columns of the image.

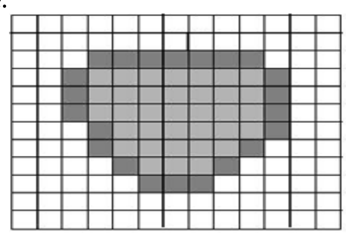

Fig 5.Boundary

The thick gray level indicates that it is boundary for the image in the above figure.1.8 Edges, lines, and points carry a lot of information about the various regions in the image. These features are usually termed as local features, since they are extracted from the local property

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 2, August 2012

alone. Though the edges and lines are both detected from the abrupt change in the gray level, yet there is an important difference between the two. An edge essentially demarcates between two distinctly different regions, which means that an edge is the border between two different regions. A line, on the other hand, may be embedded inside a single uniformly homogeneous region. A point is embedded inside a uniformly homogeneous region and its gray value is different from the average gray value of the region in which it is embedded. This is analogous to a spike. The changes in the gray levels in case of a perfect step edge, line, ramp edge are shown in the form of an edge profile in Figure 1.6. The diverse forms and nature of ideal edges and lines, such as step edge, ramp edge, line, step line.

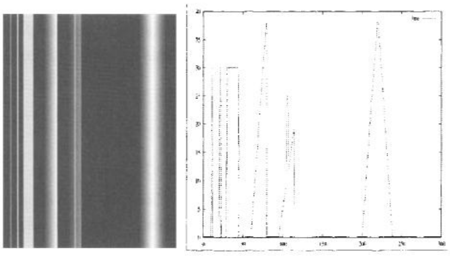

Fig 6. Edge Profile of One Row of a Synthetic Image

Edge enhancement filters, enhances the local discontinuities at the boundaries of different objects (edges) in the image. An edge in a signal is normally defined as the transition in the intensity or amplitude of that signal.

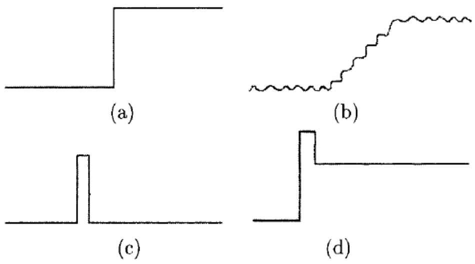

Fig .7 Different Types of Edges: (A) Step, (B) Ramp, (C) Line, (D) Step-Line.

The edge enhancement filters are divided in the following groups: Gradient (Roberts, Prewitt, Sobel, and Pixel Difference), Laplacian.

II. EDGE DETECTIONS

Gradient: The change in intensity level is measured by the gradient of the image. Since an image f(x,y) is a two dimensional function, its gradient is a vector

$$\begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{df}{dx} \\ \frac{df}{dy} \end{bmatrix}$$

The magnitude of the gradient may be computed in several ways

$$\left.\begin{aligned} G[f(x,y)] &= \sqrt{G_x^2 + G_y^2} \\ G[f(x,y)] &= |G_x| + |G_y| \\ G[f(x,y)] &= max\,\{|G_x|, |G_y|\} \end{aligned}\right\}$$

(2.1)

Gradient operators require two masks, one to obtain the X-direction gradient and the other to obtain the Y-direction gradient. These two gradients are combined to obtain a vector quantity whose magnitude represents the strength of the edge gradient a t a point in the image and whose angle represents the gradient angle. Figure 2.3 shows the gradient images of a checker board image along horizontal, vertical directions, and also along both the directions.

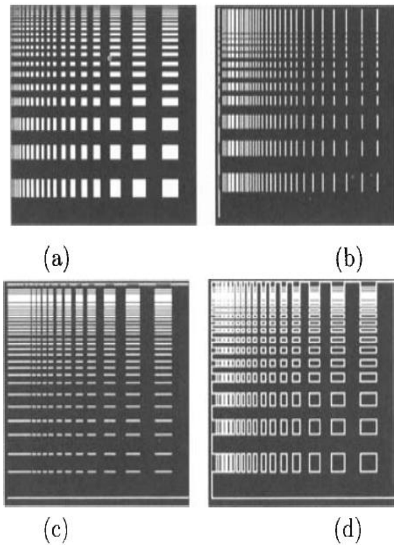

Fig .8 (A) Input Image, (B) Vertical Edges, (C) Horizontal Edges, (D) Edge Image Along Both Directions

A number of edge detectors based on a single derivative have been developed by various researchers. Amongst them most important operators are the Robert operator, Sobel operator, Prewitt operator, canny operator, Krisch operator etc. In each of these operator-based edge detection strategies, the gradient magnitude in accordance with the formula given below is computed. If the magnitude of the gradient is higher than a threshold, then edge is detected. Sobel masks are shown in Figure 11 and the edge images using sobel operator are shown in Figure 12.

1	2	1
0	0	0
-1	-2	-1

(a)

1	0	-1
2	0	-2
1	0	-1

(b)

Fig 9. Sobel Masks to Compute (A) Gradient G_x and (B) Gradient G_y

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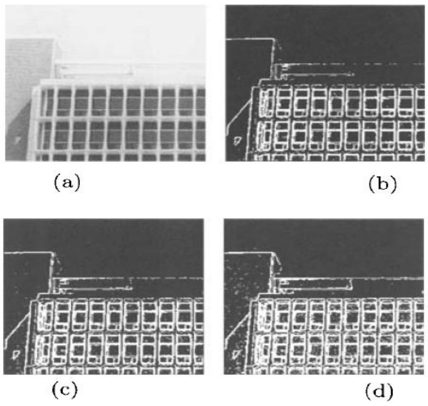

Fig 10. Edge Image using Sobel operator (a) Original image, edge detection using threshold value (b) 110, (c) 90, (d) 70.

Operators-Based On Second Derivative

The principle of edge detection based on double derivative is to detect only those points as edge points which possess local maxima in the gradient values. In this case, a peak in the first derivative and a zero crossing at the second derivative at the edge points is obtained. Hence the points at which the second derivative has a zero crossing are treated as edge points. Laplacian operator is the most commonly used second derivative-based edge operator. The gradient operators are anisotropic, i.e., they are not rotation invariant. If the isotropic operators are applied to an image and then the resultant image is rotated, it will yield the same results as rotating the image first and then applying the operator. The utility of isotropic edge operator is that direction invariant enhanced edges can be extracted. An isotropic gradient operator involves derivatives of even order. The Laplacian *operator* is one such isotropic rotation invariant operator. The corresponding convolution masks along X and *Y* directions for a 4- neighbor Laplacian impulse response is shown in Figure 10.Combining the two convolution masks in Figure 10, the gain normalized 4-neighbor Laplacian impulse response kernel may be represented as shown in Figure 12 (a). In a like-wise fashion, the gain normalized 8-neighbor Laplacian impulse response kernel is shown in Figure 12 (b).

0	0	0
1	−2	1
0	0	0

(a)

0	1	0
0	−2	0
0	1	0

(b)

Fig. 11 Laplacian Masks (A) In X-Direction, and (B) In Y-Direction.

$$\frac{1}{4}\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \qquad \frac{1}{8}\begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

(a) (b)

Fig. 12 Laplacian Impulse Response Kernels

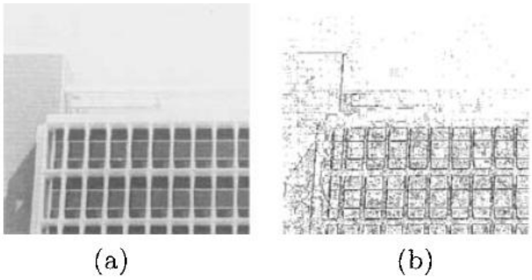

Fig. *13* (A) Original Image, (B) Edge Image by Laplacian Edge Detector

Laplacian, being the second derivative operator has zero response to linear ramp. In case of a ramp edge, it responds to the two sides, but not in the middle part of the ramp edge. The principle of edge detection based on a double derivative is to detect only those points as edge points which possess local maxima in the gradient values. Thus at edge points, a peak in the first derivative and a zero crossing at the second derivative is obtained. Hence the points at which the second derivative has a zero crossing are treated as edge points. The result of Laplacian edge detector is shown in Figure 15.

III. SYNTHETIC ARERTURE RADAR (SAR)

A. Edge Enhancement Methods:

Remote sensing plays a key role in many domains devoted to observation of the Earth, such as oceanography, cartography, or agriculture monitoring. Among the different acquisition systems, Synthetic Aperture Radar (SAR) imagery has broadly opened the field of applications in the past 20 years. This active sensor emits a microwave illumination (1–10 GHz) and measures the backscattered component. It offers the advantage of acquiring high-resolution images of the Earth's surface, in any weather conditions, both day and night. However, the main drawback of SAR is the well-known speckle corruption, inherent to any active and coherent imaging technique, which limits the analysis of the image. Segmentation is a low-level processing which helps further steps like classification or pattern recognition Actually, classical segmentation algorithms do not perform well on SAR images and a class of new methods, dedicated to speckled images, has arisen. Many techniques have been proposed, including edge detection, region growing, and random MarkovFields (RMF). For instance, the method developed by Fjortøft includes four steps: edge detection, edge extraction by watershed, region fusion, and contour refinement with RMF. Speckle-dedicated edge detectors are of special interest in SAR image segmentation because they are used in a large number of algorithms. The speckle corruption motivated the development of new edge detectors. Robust edge detection techniques are essentially based on the following two steps: edge enhancement and decision. A robust edge enhancement phase is critical in providing

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ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 2, August 2012

acceptable detection rates. This phase is usually performed through techniques that are related to derivation, namely, simple differences, Sobel filter Prewitt filter morphological gradients, etc., possibly combined with smoothing. These methods provide a limited efficiency in SAR applications due to the presence of a speckle which is a multiplicative noise like pattern the objective of this work is to design a novel method for edge enhancement in SAR images based on the exploitation of the information provided by the wavelet coefficients.

B.Existing methods for SAR imagery: Edge detectors aim at segmenting the image by finding out the transitions between homogeneous regions, rather than directly identifying them. They compute an edge strength map of the scene, in which the pixel intensity represents the ‘‘likelihood’’ of the presence of an edge at this position. This is achieved by scanning the image with an analyzing window split in two half-windows and evaluating for each position the similarity between the pixels within the two half-windows.

C. Differential Edge Detectors: Classical edge detectors are based on the difference of average intensity computed in each half-window; for that reason, they are said to be differential. The most basic one, comparable to the Prewitt filter has the following response:

$$d = |m_2 - m_1| \quad (3.1)$$

Where m1 and m2 are the average intensities computed in the two half windows of the analyzing window. They just differ by the shapes of their analyzing window, which are determined to optimize given heuristically criteria. It has been shown that differential edge detectors are not adapted to speckled images. This is due to the fact that speckle can be modeled as a random, exponentially distributed, multiplicative noise, whereas these detectors are designed for additive Gaussian noise. As a result, their false-alarm rate is non-constant but depends on the mean intensity of the region. A simple way of overcoming this problem is to apply the logarithmic transformation I→log I to the original image. In particular, one can define a detector whose response is

$$d_{log} = |m'_2 - m'_1| \quad (3.2)$$

Where m'_1 and m'_2 represent the average intensities in the half-windows after the logarithmic transformation. Because of this processing, the speckle becomes additive and differential edge detectors have a constant false alarm rate (CFAR) (see Fig. 14 c).

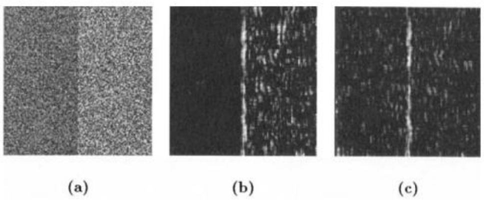

Fig 14 (A) Speckled Image with an Edge; (B) Edge Detection with D. The False alarm Rate depends On the Mean Intensity. (C) Edge Detection with D_{log}. The False Alarm Rate Is Constant.

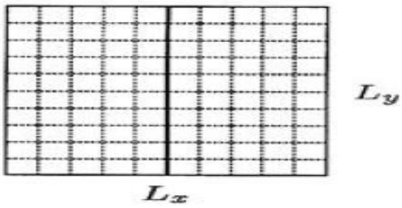

Fig 15 10x10 analyzing window (L_x x L_y rectangle)

D. Ratio Edge Detectors: Ratio-based edge detectors estimate edge strength at any pixel of interest in an image by calculating the ratio value *R* of averages of pixel values in two adjacent and non-overlapping regions, selected on opposite sides of a pixel of interest. Then the edge strength *r* is obtained as the minimum between R and R^{-1}. The edge pixel location may be determined by using ratio threshold. The detectors determine edge pixel location if $r < T$, where is the predefined ratio threshold. Tupin put forward two edge detectors based ratio, named D1 and D2 Detectors separately, and then detected linear features by fusing the two detectors. The two detectors are similar, because D2 takes the standard deviations into account besides the means of two neighborhoods as D1. In 1988, Touzi et al have tested that the ratio of averages (RoA) edge detect operator for SAR imagery is constant false alarm rate (CFAR). The RGoA method combine RoA detector with gradient edge strength information in order to improve the edge detector's performance in the presence of spatially correlated multiplicative noise. But all of these detectors need one or more thresholds, which are generally predefined or selected by experiments, *proposed method:* A novel method for edge enhancement in SAR images which uses stationary wavelet, log transforms and works for any type of edge is proposed. The method uses Haar wavelet transform for multiscale analysis.

IV. WAVELETS

Introduction to wavelets: Wavelet transform (WT) to analyze non-stationary signals, in wavelet analysis fully scalable modulated window is used. This window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time frequency representations of the signal, all with different resolutions. Because of this collection of representations we can speak of a multi-resolution

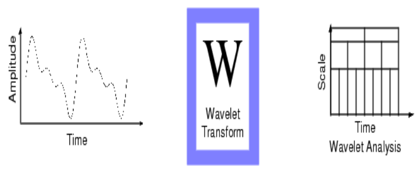

Fig 16 Illustration of Wavelet Transform

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 2, August 2012

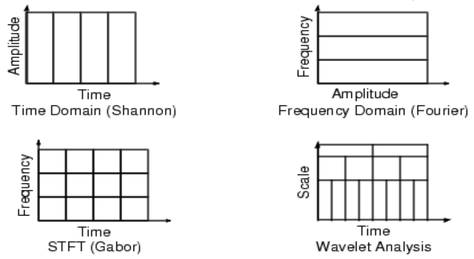

Fig 17 Time-based, Frequency-based, STFT, Wavelet Analysis

In the wavelet analysis although the widths and heights of the boxes change, the area is constant. At higher frequencies the width of the boxes decreases, i.e., the time resolution gets better and the heights of the boxes increase, that is the frequency resolution gets poorer. In STFT analysis the time and frequency resolutions are determined by the width of the analysis window, which is selected once for the entire analysis, that is both time and frequency resolutions are constant. Therefore the time-frequency plane consists of squares in the STFT case.

Continuous wavelet transform: The wavelet analysis is done in a similar way to the STFT analysis, in the sense that the signal is multiplied with a function, {the wavelet}, similar to the window function in the STFT, and the transform is computed separately for different segments of the time-domain signal. However, there are two main differences between the STFT and the CWT:

1. The Fourier transforms of the windowed signals are not taken, and therefore single peak will be seen corresponding to a sinusoid, i.e., negative frequencies are not computed.
2. The width of the window is changed as the transform is computed for every single spectral component, which is probably the most significant characteristic of the wavelet transform.

The continuous wavelet transform is defined as follows

$$CWT_x^{\psi}(\tau,s)=\Psi_x^{\psi}(\tau,s)=\frac{1}{\sqrt{|s|}}\int x(t)\,\psi^*\left(\frac{t-\tau}{s}\right)dt \qquad (4.1)$$

As seen in the above equation, the transformed signal is a function of two variables, τ and s, the translation and scale parameters, respectively. ψ (t) is the transforming function, and it is called the mother wavelet. The term mother wavelet gets its name due to two important properties of the wavelet analysis as explained below:

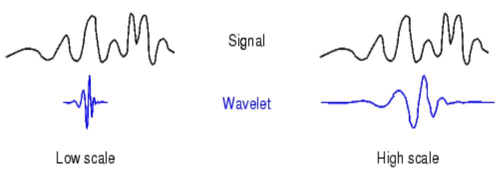

Fig 18 Wavelet at Low, High Scales

Discrete Wavelet Transform: The DWT has several characteristics that make it suitable for fulfilling some of the requirements set. The forward 1-D DWT at the encoder is best understood as successive applications of a pair of low-pass and high-pass filters, followed by down sampling by a factor two (i.e., discarding odd indexed samples) after each filtering operation as shown in Figure 5.4. The low-pass and high-pass filter pair is known as analysis filter-bank. The low-pass filter preserves the low frequencies of a signal while attenuating or eliminating the high frequencies, thus resulting in a blurred version of the original signal. The filter samples that are output from the forward DWT are referred to as wavelet coefficients. Because of the down sampling process, the total number of wavelet Coefficients is the same as the number of original signal samples.

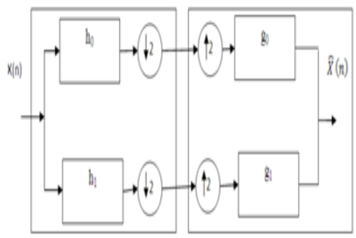

Fig 19 1-D, 2-Band Wavelet Analysis and Synthesis Filter Bank

When the DWT decomposition is applied to sequences with an odd number of samples, either the low-pass or the high-pass sequence will have one additional sample to maintain the same number of coefficients as original samples. The (h_0, h_1) filter pair is designed in such a manner that after down sampling the output of each filter by a factor of two, the original signal can still be completely recovered from the remaining samples in the absence of any quantization errors. This is referred to as the perfect reconstruction (PR) property. Reconstruction from the wavelet coefficients at the decoder is performed with another pair of low-pass and high-pass filters (g_0, g_1), known as the synthesis filter-bank. The down sampled output of the low-pass filter h_0(n) is first up sampled by a factor of two by inserting zeros in between every two samples. The result is then filtered with the synthesis low-pass filter, g_0(n). The down sampled output of the high-pass filter h_1(n) is also up sampled and filtered with the synthesis high-pass filter, g_1(n). For perfect reconstruction, the analysis and synthesis filters have to satisfy the following two conditions:

$$H_0(z)G_0(z) + H_1(z)G_1(z) = 2 \qquad (4.2)$$

$$H_0(-z)G_0(z) + H_1(-z)G_1(z) = 0 \qquad (4.3)$$

Where H_0(z) is the Z-transform of h_0(n), G_0(z) is the Z-transform of g_0(n), etc.

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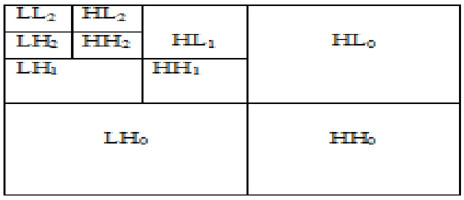


Fig 20 2-D, 3-Level Decomposition Using DWT

The Haar mother wavelet is defined as follows:

$$\Phi_0(t) = \begin{cases} 1 & 0 \le t \le 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\Psi_0(x) = \begin{cases} 1 & 0 \le t \le \frac{1}{2} \\ -1 & \frac{1}{2} \le t \le 1 \\ 0 & \text{otherwise} \end{cases} \quad (4.4)$$

Stationary Wavelet Transform:

The SWT up samples the coefficients of the lowpass and high pass filters at each level. The up sampling operation is equivalent to dilating wavelets. The resolution of the SWT coefficients decreases with increasing levels of decomposition. The key point is that it is redundant, shift invariant, and it gives a denser approximation to the continuous wavelet transform than the approximation provided by the orthonormal (ON) discrete wavelet transform (DWT). Form the filter bank point of view, we keep both even and odd down samples, and further split the lowpass bands.

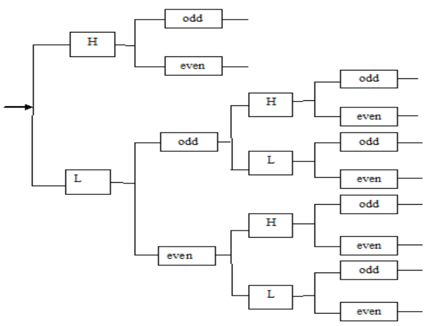


Fig 21 Diagram for Stationary Wavelet Transform

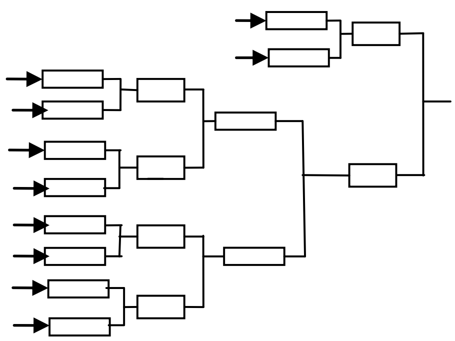


Fig 22 Diagram for the two levels Inverse Stationary Wavelet Transform

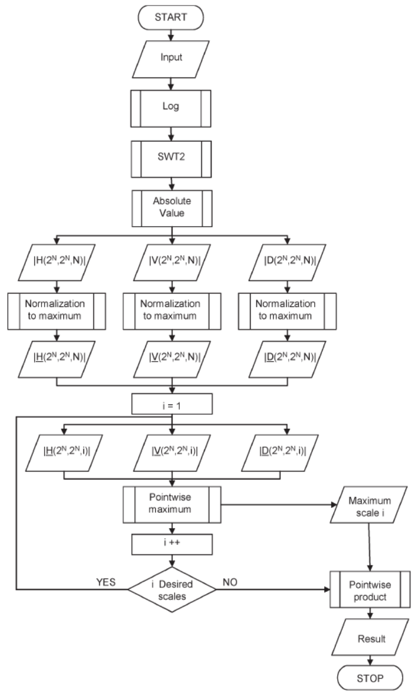


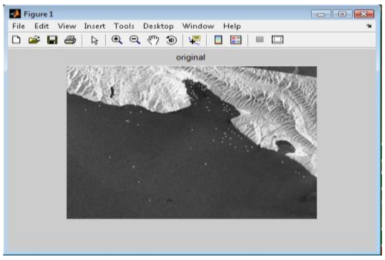
Fig 23 Flowchart of the Edge Enhancement Algorithm

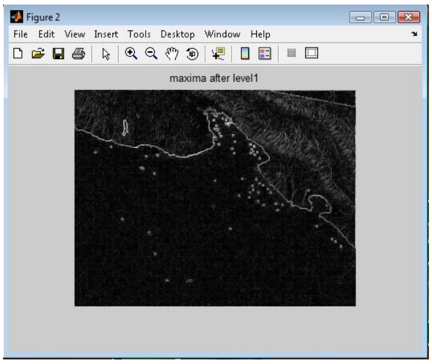
The algorithm for edge enhancement in SAR images, which is proposed in this paper, relies on the difference of behavior along the wavelet scales of the speckle in front of the edges. On the one hand, the discontinuities are highlighted by the wavelet transform, and they tend to persist over scales .On the other hand, the speckle is progressively smoothen, and moreover, it is almost spatially uncorrelated between scales. In the first step the logarithm transformation is applied to the original signal in order to make the multiplicative speckle to Gaussian additive and signal independent. This operation is also helpful in reducing the large dynamic range of SAR data. The flowchart of the proposed algorithm is shown in Fig 5.8. After the logarithmic operation SWT in two dimensions is applied, three band pass components are obtained, where each one enhances the discontinuities in a different direction. After normalizing each of these sub bands to their maximum and taking their absolute value, the point wise maximum across all of the three sub bands is evaluated. A correct implementation of the algorithm proposed here must also deal with situations where a sub band does not contain a vessel, as the proposed normalization may lead to noise amplification. Then, the different intermediate maxima previously calculated are combined through point wise multiplication. If necessary and if some kind of a priori information is available, the number of iterations can be adjusted accordingly. The first important property of the proposed algorithm is simplicity. The proposed technique is simple, and its computational cost is low. It is an iterative process just requiring the following two operations per iteration: the application of a single iteration of the SWT and the

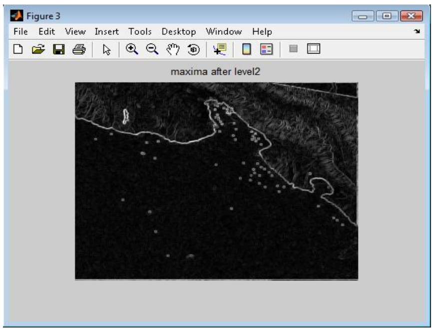
ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 2, August 2012

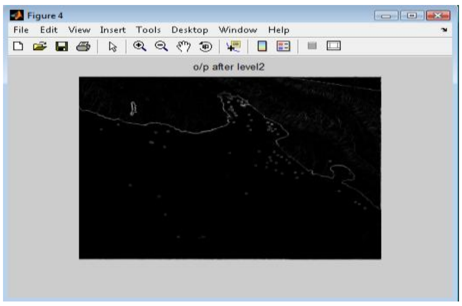
evaluation of the point wise maxima. No previous radiometric calibration is required. Since this application is not concerned with a precise retrieval of radar cross section values but just with contrast in intensity. One of the main interests of the algorithm is that it provides a result directly in the wavelet domain. As a consequence, contrary to conventional filters, it does not require any inversion step, which is usually an awkward process, often introducing artifacts when wavelet coefficients are processed. The proposed method can be essentially employed for automatic coastline detection in SAR images and automatic ship detection.

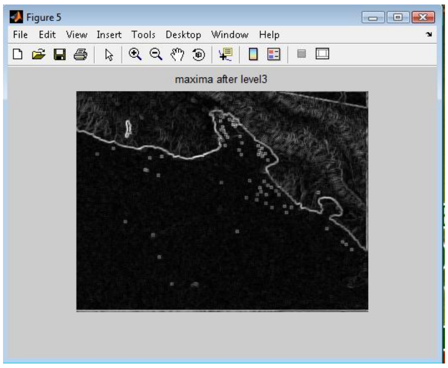
V. OUTPUT SCREENS

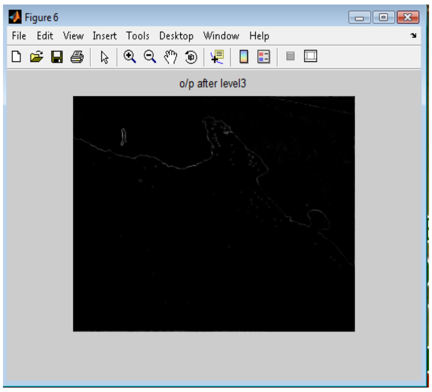












VI. CONCLUSION & FUTURE WORK

The method proposes a robust edge enhancement directly in the wavelet transformed domain, The edge enhancement phase has been proven to be critical in heterogeneous SAR images, and the original method proposed in this paper constitutes a good solution that is used to deal with this type of data. It does not require any type of prefiltering of data, and it is independent of the statistics of the input image. The adaptation capability of the method to very diverse scenarios with no need of *a priori* knowledge or settings is a useful feature in view of its integration in an unsupervised segmentation. As future work curvelet, contourlet transforms can be used instead of wavelet transform to improve the performance of the algorithm. The normalization technique which is invariant to translation, rotation, scaling can be used such that the algorithm will be much more effective.

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ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 2, August 2012

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