Using Wavelets as an Effective Alternative Tool for Wind Disaster Detection from Satellite Images

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ABSTRACT: Tropical cyclones have been factors in many natural disasters that have occurred in the past few decades. Time delay in identifying the wind damage locations has made these disasters much worse. Quick identification of damage locations enable rapid relief efforts and thus reduce the impact of such disasters. Developments in the computational field have enabled this to be achieved by appropriate utilization of high resolution satellite image features by extraction and classification and finally identifying the damage location and thereby providing immediate aid. It will also facilitate appropriate maintenance to partially or completely destroyed building structures.

This paper describes the detection of the hurricane-prone building disasters from satellite images of the shores of Punta Gorda before and after the Hurricane ‘Charley’ 2004 disaster, as this damage account for one of the dreadful tropical cyclone damages that has occurred. The computational analysis used the latest feature extraction technique: wavelet feature extraction. Buildings are categorized into different damage levels based on the ground truth data and the RS-Scale (Remote Sensing Scale) table. Results were obtained from wavelet feature extraction of the statistical characteristics of the image pixel radiance value, such as standard deviation and maximum value, and also of image characteristics such as edge intensity factor. A comparison analysis was also done by comparing these results with those obtained using conventional extraction techniques. It is observed that the different damage levels of buildings had superior identification information when extracted using the wavelet feature extraction technique rather than the information obtained using conventional extraction techniques.

1 INTRODUCTION

From cave dwellings to the present day, wind disaster and damage to structures and buildings has been a fact of life. A bar chart provided by the Swiss Reinsurance Company, which charts the world’s insurance losses from Major Natural Disasters (1970-1999), showed a dramatic increase from 1987 onwards. Wind storms accounted for about 70% of the total insured cost and the majority of these, have been caused by tropical cyclones. Of the dreadful hurricanes of the 2004 Atlantic hurricane season, Hurricane Charley was the third named storm and the second major hurricane. It made landfall on Friday, August 13, 2004 on the southwest coast of Florida at Charlotte Harbor. It was the strongest hurricane to hit the United States since Hurricane Andrew struck Florida twelve years earlier in 1992, with a wind speed of 240 km/h at peak intensity, making it a strong Category 4 hurricane on the Saffir-Simpson Hurricane Scale. It also became the second costliest hurricane in United States history, with estimated damage of $15.4 billion, after Hurricane Andrew (Womble 2005).

Obtaining information on such catastrophic damage from ground surveys (ground truth data) is time consuming and costly. To achieve a quicker response and thus provide instant help to widely damaged locations, computational analysis will become necessary. Exploitation of remote sensing technology along with the latest pattern recognition knowledge and image processing techniques creates a new route for such computational analysis.

Past researches have been done on other types of natural disasters such as earthquakes using aerial images (Hasegawa et al 2000, Mitomi et al 2001, Sumer et al 2004 and Ozisik D 2004), and a major contribution using Satellite Imagery was done by Matsuoka et al 2000 and Vu et al 2005. Researches have also been done on other natural disasters such as wild fires (Ambrosia et al 1998), floods (Groeve et al 2009), landslides (Danneels et al 2008) and so on by computational identification using low-resolution satellite images. But the introduction of high resolution satellite imageries has created a breakthrough in identification of disaster affected areas for rescue purposes as well as reconstruction of wind disaster damaged buildings. In Womble et al 2007 and Womble 2005, computational analysis was done on building damage detection mainly using conventional statistical analysis of the histogram of the satellite image pixel radiance value. Damage to building structures is rated by ground truth data into an RS-Scale (Remote Sensing Scale) table. More accurate and faster damage identification will save more lives and more building structures will be restored faster. Wavelet, a novel technique for pattern recognition (instead of conventional statistical analysis) of high-resolution satellite images has been introduced to identify damaged buildings after the passage of a hurricane.

2 METHODOLOGY

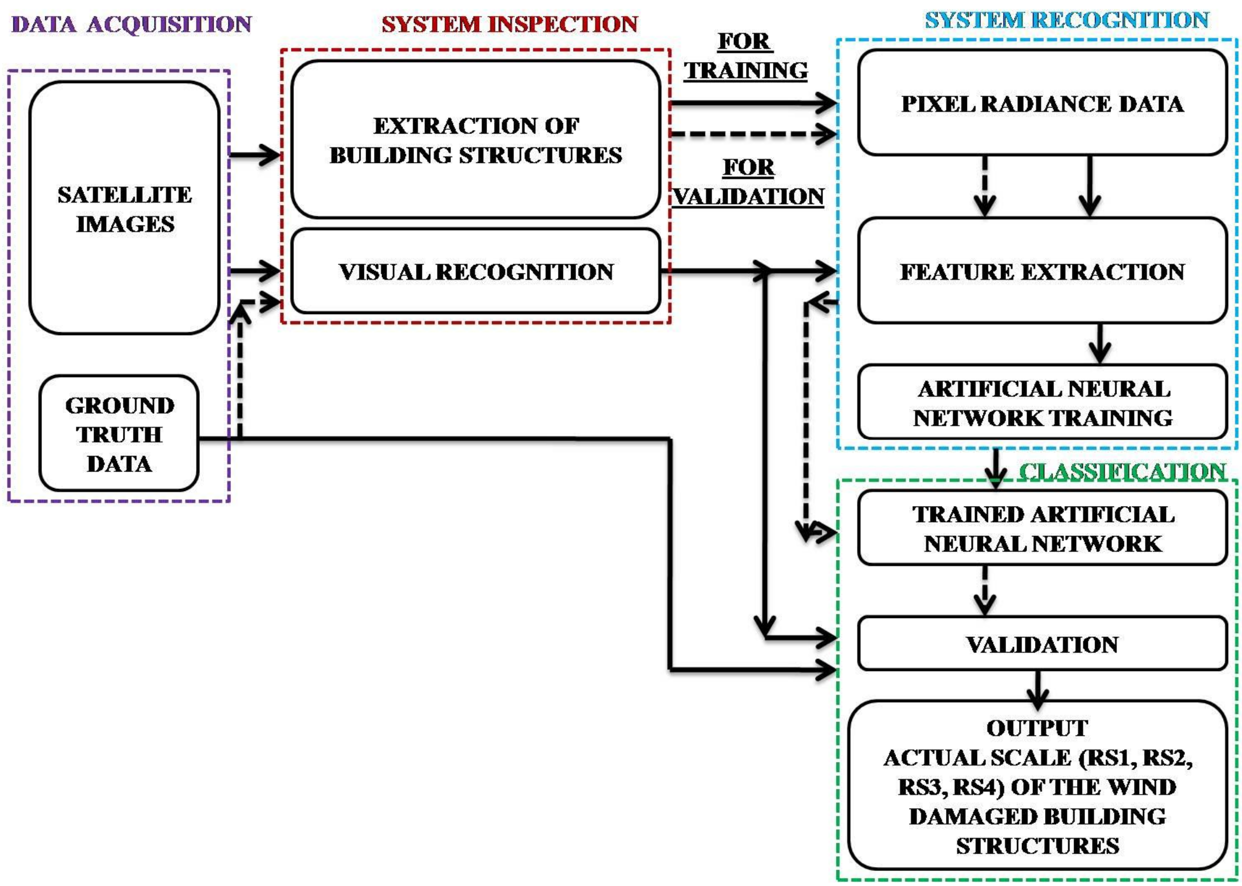


Figure 1. Block Diagram Representation of Experimental Procedure

Figure 1 shows a block diagram representation of the entire experimental procedure for wind disaster area detection from a satellite image. The procedure includes the following steps: Data Acquisition, System Inspection, System Recognition and finally Classification.

2.1 *Data Acquisition*

Information is acquired in two main formats, satellite imageries of the disaster location, Punta Gorda, FL (Florida), United States, before and after the hurricane and also ground truth information.

Two QuickBird Satellite Imageries of the disaster location, Punta Gorda, FL, before and after the hurricane were obtained from DigitalGlobe Co., Ltd., and licensed and provided by the Remote Sensing Technology Center of Japan (RESTEC). These provided wider coverage of information about the area where the hurricane had a severe impact than a conventional field investigation could have. Figure 2(b) shows the multi-spectral post-storm imagery (Post-Disaster Image), taken on August 14, 2004, just a day after the hurricane's landfall. Figure 2(a) shows the multi-spectral pre-storm imagery (Pre-Disaster Image), taken on March 23, 2004.

Figure 2(a). Pre-Disaster Image

Figure 2(b). Post-Disaster Image

(Purchased from DigitalGlobe Co., Ltd)

The main objective of ground truth information is to validate the results obtained from pattern recognition of 4 different RS Scale classes: RS1, RS2, RS3 and RS4 (RS Scales are detailed in Table 2), of wind damaged buildings. This information also aids in selection of RS Scale classes of wind damaged buildings for training the classifier, Artificial Neural Network (ANN), also through visual inspection. Ground truth information is usually very limited due to time restrictions and inaccessibility of the disaster location just after such a major wind disaster event.

2.2 *System Inspection*

After data collection, the satellite images are subjected to system inspection. Initially, the two images are subject to image registration (Lakshminarasimhan 2004) and then buildings are identified from the images and collected as separate RS scaled samples for system recognition. Visual recognition from satellite images also helps in this step of system inspection, aided by available limited ground truth information. The samples are obtained for two purposes. The feature extracted from the first set of samples is used for training the ANN classifier and the feature extracted from the second set is used for validation.

2.3 *System Recognition*

After obtaining the building image samples by system inspection, they are subjected to an automated system recognition procedure. This procedure extracts the main features and finally identifies the RS scale classes using the ANN classifier.

2.3.1 *Feature Extraction from Pixel Radiance Data*

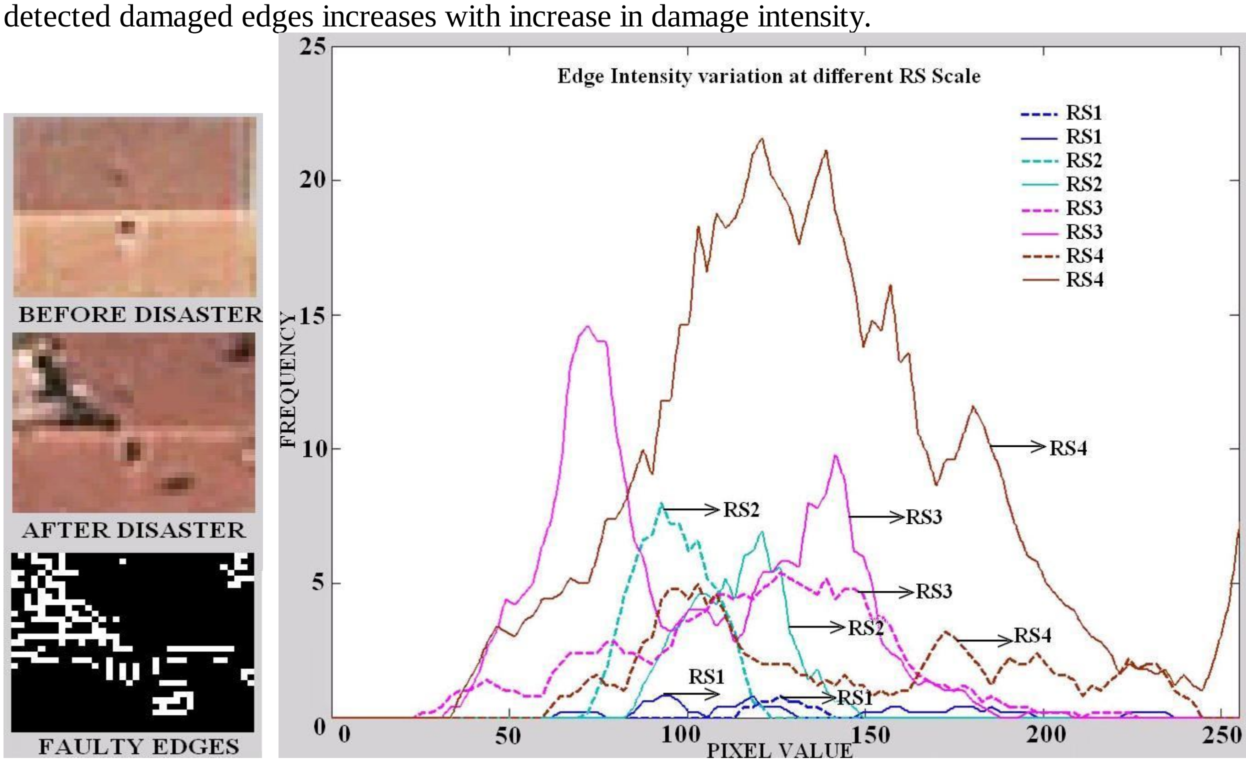
Raw pixel radiance data from all image samples with three visible channels, Red, Green and Blue (RGB channels or bands), of 16-bit QuickBird imageries collected, contains a lot of hidden features, which have to be extracted to get the required identity of the damage condition of each building. In this experiment, the ordinary feature extraction approach as well as the latest wavelet extraction approach is used. The wavelet feature extraction approach is detailed in section 3 of this paper. The conventional approach is done using the following two methods.

2.3.1.1 Statistical Feature Extraction

The major contributing features for identifying the different RS Scale classes of wind damaged building structures are standard deviation (Womble 2005) and peak values extracted from the pixel radiance information from the collected building image samples. It is observed that the standard deviation and (peak) maximum value increase with the increase in the damage intensity.

2.3.1.2 Image Feature

The major contributing image feature for identifying the different classes of wind damaged building structures directly and quickly is its edge intensity. An edge in an image is a contour across which the brightness of the image changes suddenly. In this experiment, ordinary edge detection is done using a Prewitt operator. The Prewitt method finds edges using the Prewitt approximation of the derivative. It returns edges at those points where there is a maximum intensity gradient. Figure 3(a) gives an example house with detected faulty edges and Figure 3(b) shows the histogram distribution of different damage RS scale classes of a few examples of the damaged building samples extracted from the satellite images. It is observed that the histogram distribution of the detected damaged edges increases with increase in damage intensity.



3(a) 3(b)

Figure 3. Edge detection using Prewitt approximation, 3(a) Example house with detected damaged (Faulty) edges and 3(b) Histogram distribution of different Remote Sensing (RS) damaged scale classes RS1, RS2, RS3 and RS4 of a few examples of the damaged building samples extracted from the satellite images.

2.3.2 *Artificial Neural Network (ANN) Training and Classification*

ANN is one of the latest approaches to prediction and evaluation using computer models with some of the architecture and processing capabilities of the human brain. ANN is made up of processing elements called neurons, which are arranged mainly in three layers: input layer, hidden layer and output layer. In the current experiment, the back propagation method (Radhika et al 2009) of ANN was used. The training network is designed with 9 input nodes, 11 hidden layer nodes and one output node. The features extracted from the first set of samples of different RS scaled damaged building images are the input to the input nodes for training the ANN network and that of the second set of samples were used to validate the classification. The output node displays which RS scale the validation samples belong to, after classification.

3 WAVELETS

Various feature extraction methods have been used in the past for different types of fault classification, such as histogram, multifractal, statistical feature extraction methods, etc. (Sabareesh et al 2006 and Douglas et al 2005). Of these, only the ordinary statistical feature extraction technique has been used in the field of wind damage detection from satellite images (Womble et al 2007 and Womble 2005). In all these methods, either spatial domain information or frequency domain information is available at one time, not both together. Thus, there is a greater chance of losing major information regarding the signal. Feature extraction using wavelet transform aids in gathering the spatial as well as the frequency domain information together (Radhika et al 2009).

3.1 *Best Wavelet Selection*

The family of discrete wavelets used in the present case includes, Daubechies, Coiflets, Symlets, Discrete Meyer and Biorthogonal. Experiments were done to find out the best wavelet for identifying the pattern of a particular damage scale. The correct pattern is identified based on the maximum % margin of separation between the two least different RS scales (RS1 and RS2). *Margin of separation* is the margin drawn in between two different classes in order to separate them from each other. The larger the distance between two classes, the larger will be the margin of separation and the more accurate will be the classification. A Biorthogonal wavelet has successfully recognized the damaged edges and the standard deviation distribution and the Daubechies wavelet has recognized the peak value of the damaged area.

3.2 *Wavelet Feature Extraction*

In this paper, as the data is a two-dimensional imagery, two-dimensional discrete wavelets are used. The two-dimensional discrete wavelet transform leads to a decomposition of approximation coefficients (CA_j) at level ‘j’ in four components: the approximate coefficient at level j + 1(CA_{j+1}), and the detailed coefficients at level j + 1 in three orientations (CD_{j+1}). The basic decomposition steps are described in Figure 4. Lo_D indicates a low-pass decomposing filter and Hi_D indicates a high-pass decomposing filter. For statistical feature extraction, a comparison of the maximum % margin of separation between the extracted features of two different RS scales (for e.g.: RS1 and RS2) extracted by the conventional statistical method and the wavelet extraction method is done in order to determine an efficient feature extraction method, with which the identification and classification of different scales of wind damaged building images from satellite images speeds up.

For image feature extraction, i.e. for edge intensity extraction using wavelet method, the detailed coefficients up to level 2 are fused with the original imagery, so as to extract the high frequency image information. The high frequency information within the image stores the precise data on edge intensity, with which the error in detecting the edges is reduced tremendously.

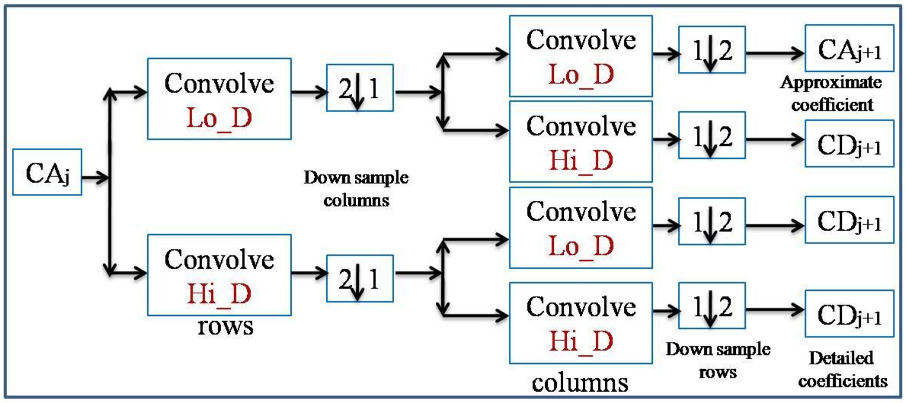


Figure 4. Basic two-dimensional wavelet decomposition steps.

4 RESULTS AND CONCLUSIONS

4.1 *Comparison of % margin of separation of Statistical features With and Without Wavelets*

The % margins of separation of standard deviation features with and without wavelets for RGB channels or bands and vision layer are compared and it is observed that when wavelet feature extraction is used the % margin of separation is greater than with conventional feature extraction. The results are listed in Table 1. The higher the % margin of separation, the more accurate the classification. A similar observation is obtained for maximum value feature.

Table 1.% Margin of separation for Std dev feature

RS Scales %	Without wavelet %	With wavelet
RED BAND		
RS1&RS2	36	57
RS2&RS3	53	56
RS3&RS4	23	27
GREEN BAND		
RS1&RS2	26	34
RS2&RS3	43	53
RS3&RS4	47	56
BLUE BAND		
RS1&RS2	25	32
RS2&RS3	39	43
RS3&RS4	54	69
VISION LAYER		
RS1&RS2	37	57
RS2&RS3	53	56
RS3&RS4	24	28

5 (a)   5 (b)   5 (c)

Figure 5. Example house 5 (a) with detected damaged edges, with wavelet 5 (b) and without wavelet 5 (c)

4.2 *Comparison of Image features With and Without Wavelets*

It is observed that on edge detection using wavelets the errors are reduced, i.e. some of the edges which are not broken are identified as broken edges when using Prewitt operator. But on edge detection using Biorthogonal wavelet, edges are correctly identified (Figure 5).

4.3 *Feature Classification and Validation With and Without Wavelets*

After the extraction of the required features, by both the conventional method and the wavelet method, the samples are identified for different RS Scales. Figure 6 shows some samples selected for training, validation and identification using ground truth data.

Similarly, identification is done for all other samples used in this experiment and results as % of accurately identified samples into its exact RS scale are listed in Table 2.

6(a)

	House No	Visual Recognition	System recognition Without Wavelet	System recognition With Wavelet	Ground truth Data
Few Samples for Training	Hse 6	RS-1	RS-1	RS-1	NA
	Hse 8	RS-1	RS-1	RS-1	NA
	Hse 3	RS-2	RS-2	RS-2	RS-2
	Hse 4	RS-2	RS-2	RS-2	NA
	Hse 1	RS-3	RS-3	RS-3	RS-3
	Hse 2	RS-3	RS-3	RS-3	RS-3
	Hse 5	RS-4	RS-4	RS-4	NA
	Hse 7	RS-4	RS-4	RS-4	RS-4
Few Samples for Validating	Hse 9	RS-1	RS-1	RS-1	NA
	Hse 11	RS-2	RS-1	RS-2	RS-2
	Hse 10	RS-3	RS-2	RS-4	NA
	Hse 12	RS-4	RS-4	RS-4	NA

6(b)

Figure 6. Sample buildings and their classification. 6(a) A portion of satellite imagery, showing sample house selected for training in red rectangular boxes and that for validation in yellow rectangular boxes. 6(b) ANN Classification and Identification of RS scales with and without wavelets for some sample houses and validation using visual recognition and ground truth information. (Satellite Imagery Purchased from DigitalGlobe Co., Ltd)

Table 2.% of Accurate identification of Samples of RS Scaled images

RS Scales	Without wavelet %	With wavelet %	Building Condition
RS1	100	100	No obvious damage
RS2	60	90	Roof Shingles removed, deck exposed
RS3	50	80	Deck removed , roof structure exposed
RS4	90	100	Completely collapsed

4.4 *Conclusions*

Wind damage to building structures is successfully identified from statistical and image features extracted from pre-disaster and post-disaster satellite images, both by conventional method and by wavelet extraction method. Classification of identified building structures into different scales in the Remote Sensing perspective (RS Scale-RS1, RS2, RS3 and RS4) achieved using the wavelet feature extraction technique is proved to be an enhanced result, rather than the conventional statistical method as the % margins of separation between different RS Scales obtained using wavelet is larger than that obtained from the conventional method. The larger the % margin of separation the more accurate the classification. The wavelet extraction technique also aided in identifying broken edges with minimum error compared to the conventional Prewitt operator for edge detection. Thus, accurate identification is achieved by using Wavelet Feature Extraction, thereby making wind disaster mitigation quicker and more efficient.

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