RAPID DEBRIS ESTIMATION AFTER HURRICANE DAMAGE IN URBAN AREAS USING HIGH RESOLUTION AERIAL IMAGERY

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ABSTRACT

Recent hurricanes have severely impacted communities in the southeast Gulf and Atlantic coasts. As part of each state's response to natural disasters that affect urban areas, there is a need to support local governments with timely information on the extent and location of damage. Identifying post-hurricane downed trees by remote sensing is difficult in forests because they can be hidden by standing tree canopies. Urban trees are usually open-grown and adjacent to buildings, infrastructure and other vegetation, thus making it easier to distinguish them post-hurricane. We developed an assessment tool to estimate downed tree debris in hurricane affected urban areas based on Leica Airborne Digital Sensor (ADS40) very high resolution digital images. A Sobel edge detection algorithm was combined with spectral information based on color filtering with 15 different statistical combinations of RGB bands to detect downed trees. The Sobel method identifies downed tree edges based on contrasts between downed tree stems and grass or asphalt. Color filtering was then used to establish a threshold value where every color above or below a certain value was replaced and excluded from the identification processes. The results of the methods were overlaid and where lines (edges) from longer consecutive segments and color values within the threshold were met; an "edge line" was placed. Where two lines were paired within a very short distance in the scene a polygon was drawn automatically and, in doing so, downed tree stems were detected. The developed algorithm successfully detected downed trees and determined their diameter. Diameter data was then used to estimate volumes of post-hurricane downed tree debris.

Keywords: hurricane debris, edge detection, color filtering, urban forests

OBJECTIVES

Hurricane Ivan caused an estimated $14 billion in damage in the United States alone (http://www.ncdc.noaa.gov/oa/reports/billionz.html#chron), making it the third costliest hurricane on record at the time. Pensacola, FL found itself on the eastern side of the eye wall, which sent a large storm surge and strong winds into Escambia Bay that eventually destroyed most of the urban trees, and dwellings. Existing (hard truth) field data was collected by University of Florida researchers (Duryea, et al., 2007) in the Florida Panhandle including Pensacola, two days after Hurricane Ivan. Escobedo et al (2009) assessed community-wide debris following the 2004-2005 hurricanes seasons. Their measurements give a set of unique conditions that have resulted in measurable urban forest damage and costs. However, ground truth data collection is very costly and time consuming. Clearly, there is a need to support local governments with timely information on the extent and location of damage to urban forests. Remote sensing can be used to develop a rapid image recognition system.

Post-hurricane imagery is a promising method to perform automatic recognition of downed trees and estimate their volume. Similar remote sensing based studies have been done for determining characteristics in - object-based analyses of forest vegetation (Mallinis et al., 2008), estimation of aboveground biomass (Okuda et al., 2004), spatial and spectral differences of tree crowns (Sugumaran, et al., 2003), and individual tree species comparison (Key et al., 2001). However, to our knowledge there is no research on urban tree debris estimation using very high resolution digital sensor data has been done. Barnes et al., (2007) developed an image-driven data mining approach with sigma-tree structure, which they tested with IKONOS multispectral (2x2m RGB and NIR) and IKONOS-2 (1x1m) panchromatic images. Their method yielded 70 % detection of trees and 82 % of grassy areas of user's accuracy which is the probability that a pixel classified in the image is really a member of the assigned class. However, they do not clarify that they were detecting standing or downed trees.

Sugumaran et al., (2003) used spatially enhanced high resolution IKONOS multispectral imagery (1x1m) and 25 cm and 1 m airborne images for urban forest crown identification. However, Gougeon (2000) suggested, that images with 1 m resolution are more suitable for such applications than higher spatial resolution images. Sugumaran et al., (2003) employed traditional classification (maximum likelihood) and rule based (classification and regression tree – CART) methods, both with training data. Maximum likelihood classifier is purely relying on the image's spectral information while CART requires combined spectral and ancillary data for the classification. They found that 1 m spatial resolution aerial and satellite imagery taken in a certain time of the year (September) were useful in identifying tree crowns of oak species. On the 25 cm spatial resolution images the trees are seen very clearly but the number of shadow pixels increased, while on the 1 m resolution images the tree crowns could be identified without a shadow effect.

Other method includes Geographic Information System (GIS) based approaches. Pickens et al., (2000) was trying to identify damaged forested areas which had 75-100% downed trees after Hurricane Fran in North Carolina. Although, they were more interested in pre-suppression fire planning rather than estimating a debris volume, they "heads up" digitizing of damaged areas. Later in an additional study they created a map using ArcGIS Spatial Analyst where GPS points were collected and Inverse Distance Weightened interpolation method was employed to predict damaged areas.

Another study, also from North Carolina, approached similar problems in a slightly different way. After Hurricane Isabel blew through Petersburg National Battlefield, scientists (Shedd et al., 2005) proposed to estimate the woody debris. ArcGIS' object oriented classifier; Feature Analyst (FA) was employed in their research. They used small scale (1:6000) digital aerial photos where true color and color infrared imagery were captured. Using traditional techniques such as supervised and unsupervised classification, Leaf area index and Normalized Difference Vegetation Index (NDVI) helped to identify downed woody debris. However, the spectral responses alone could not quantify all areas of woody debris and they used ArcGIS Feature analyst which focuses not only on spectral characteristics but on the recognition on spatial patterns as well. While FA could map downed areas well, it could not quantify the downed woody debris.

Studies have been done in estimating above ground biomass, but most of them are using medium resolution satellite imagery and regression techniques. Magnusson and Fransson (2005) estimated stand level tree volumes by averaging the reflectance values within a stand. Landsat bands 1,2,4,5 and 7 data was used in the regression analysis, where the R square values were above 0.90. Lefsky et al., (2001) used 1 m spatial resolution data to predict biomass with a regression model (R square = 0.47). On the other hand, using ground based data in the calculations, Jenkins et al., (2003) above ground biomass (including coarse roots) estimation model yielded very high R square values > 0.95.

It seems that spectral information is useful to identify tree stems and crowns from such an environment According to Soille (et al., 2002), "Recognition of an object simply means that all the rest has been eliminated from the scene. This is a definitive irreversible operation". Thus, two image processing techniques were used for this study: edge detection and color filtering. Edge detection should work based on the homogeneity of colors and strong contrasts identified as edges. Basic color filtering is a simple algorithm that requires a threshold value and every color above the threshold is replaced by another color, usually black. More advanced color filtering techniques will be applied to improve the response of the filtering process. Specifically color filtering combined with Euclidian distance transform should work well with a specific range of RGB values, such as the colors of tree debris. Although this project encompasses different image processing techniques, its true focus is in the application of the processed image.

Once all "noise" is eliminated from the image, an algorithm is used to calculate the mass/volume of the fallen tree debris. We employ a commonly used debris estimation formula used by USDA Forest Service Strike Teams (USDA Forest Service, 2008) to calculate woody debris volume from downed trees. Based on Federal Emergency Management Agency (FEMA) guidelines, the algorithm uses the calculated tree diameter to estimate woody debris.

Thus, our hypothesis is that we can estimate urban forest debris volume accurately, using high resolution aerial images and USDA Forest Service Centers for Urban and Interface Forestry's Ground Debris Estimation Tables (UFST) (Personal Communication, Dudley Hartel USDA Forest Service, August, 2009).

Therefore the specific objectives of this study are to: (1) detect downed trees in urban environment and (2) calculate their debris volume using spectral characteristics of the trees and a debris estimation model.

Approach

The planar rectified imagery was collected by a Leica ADS40 digital sensor by 3001 the Geospatial Company (www.3001inc.com) over areas affected by Hurricane Ivan. The ADS40 is a push-broom multi-spectral sensor developed by Leica Geosystems (Leica Geosystems GIS & Mapping LLC, Heerbrugg, Switzerland) with a 12,000 pixel swath. The sensor configuration for this collection was red-blue-green bands images taken simultaneously from a single viewing angle with airborne GPS and IMU data, which was used to georeference the raw imagery. Imagery was acquired at about twelve inches (27 cm) ground sample distance resolution. Flight height maintained during mission was about 3000 meter above ground level. The imagery (Image1 and Image2) was captured at 12-bit radiometric resolution and converted to 8-bit radiometric resolution during post processing (Figure 1A and 1B).

Figure 1A. Leica ADS40 Imagery (Image1).

Figure 1B. Leica ADS40 Imagery (Image2).

The programming aspect of the project was done using VisualStudio 2005 in C# language. AForge.Net was used for the image processing applications. AForge is an open-source framework developed by Andrew Kirillov for uses in image processing machine vision, genetic algorithm development and neural network algorithm development (www.aforgenet.com). By using the framework the focus of the project can shift from processing the data to analyzing the processed data. A statistical analysis will be done to determine the optimal values for the filtering techniques and after the filters are applied the data will be analyzed to estimate the volume/mass of tree debris in the area.

The first method examined for the project was the mathematical morphology. The simple morphologic filters are based on erosion, dilation, opening and closing operations. There are also more advanced morphologic filters but all of them have the drawback of distorting the quality of the image. (Cheng and Venetsanopoulos, 1992) Since the number of pixels is the key to determining the diameter of a trunk, any distortion would result in inaccurate measurements which are simply not acceptable for this type of project. The second technique analyzed for image processing was edge detection. The theory behind edge detection is the measure of color constancy. Changes from one color to the next are modeled as a grayscale image where the intensity of the gray line represents how large the change was from one color to the next. The grayscale image forms a realistic interpretation of most of the edges in the image (Weijer et al., 2007). Therein lays the problem with this method, since the images are of urban areas there are many edges that do not factor into the equation.

Edges such as roofs, streets, standing trees, etc. should be eliminated from the image. The last technique was color filtering in which a color threshold is selected for each channel and any color that is over the threshold is replaced by the color black. This seems to be the most logical choice since the color of the tree trunks is consistent. Although this method is not perfect since it cannot distinguish between trunks and similar color rooftops, simple boundary conditions would eliminate the errors caused by this technique.

The Euclidian distance transform has been found to improve the accuracy of color filtering techniques over a range of colors (Barni et al., 2000). Color filtering implemented with Euclidian distance transform can be viewed as creating a sphere centered at a selected "threshold" value for the RGB channels and with a radius corresponding to the range of acceptable values. For example, in this project most trunks have color values roughly 15-25 in each of the channels by centering the sphere at (20, 20, 20) with a radius of 8 all of these colors would be left with a relatively small amount of undesired colors left. If each color is represented as a vector then according to Euclidian geometry the distance to a point (in this case the center of the sphere) can be viewed as the square root of the sum of the distance squared in each axis. Mathematically the problem can be represented with the following formula (Barni et al., 2000):

$$V(\vec{v}) = \|\vec{v}\| = \sqrt{\sum_{i=1}^{n} v_i^2} \qquad \text{(E. 1)}$$

where v corresponds to the color of the pixel in question and v_i represents the difference between the center color value and the pixel color value for a specific channel. When applied to RGB color filtering n is 3 since there are three channels. The largest flaw of color filtering using Euclidian distance transform is its performance. For an nXn color image the algorithm runs in $Y(n^2)$ time and takes $Y(n^2)$ space (Sudha et al., 1998). Since efficiency and memory usage are not of large concern to the project, this algorithm satisfies the requirements of the project. The analysis of the processed image will be done through a statistical model and explained further in the algorithm development section. Once the angle between the fallen tree and the horizontal axes is found, a rectangle is drawn over the image at the same angle to encompass the whole tree including the crown. The rectangle then reduced progressively until its area's 98-99 percent is not black.

Algorithm Development (Part I). The algorithm consisted of four phases. The first phase is edge detection; the second phase is filtering based on data collection. The third phase is the analysis of the filtered image where line detection and comparison as well as polygon detection is done. The last phase is the tree diameter calculation.

The edge detection phrase employed Sobel's edge detection method (G), where

$$G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad \text{and} \quad G_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \qquad \text{(E. 2)}$$

The magnitude of the gradient is then calculated using the following formula:

$$G = \sqrt{{G_y}^2 + {G_x}^2} \qquad \text{(E. 3)}$$

Advantage of using this method is that it highlights most of the details of picture. Disadvantage is that small insignificant edges will also appear on the image **(**Gonzalez and Woods, 1992).

The data collection of the color filtering phase employs a dynamic statistical model. A dataset of acceptable points is collected by clicking on random points on the trees in the image. It is dynamic because it does not store the statistical values after they are used, making the algorithm more versatile and less susceptible to the common errors, such as varying times from local zenith or different looking angles. The data set collected is composed of maximum and minimum values for each sub color in the RGB band, YCbCr band and HSL bands. In addition the difference between RG, BR, and BG is used as the backbone of the algorithm since the strongest filter is the respective mean with twice the standard deviation (SD) for thresholds while RG difference values are taken as once the SD and BR and BG are taken as 1.5 times the SD (Table 1). The algorithm considers 15 different statistical combinations of bands to determine color filtering

Table 1. Statistical combinations of the color filtering phrase

Band	Percent Considered	Formula
Red, Green, Blue	95.45%	From image
Hue, Saturation, Luminance	95.45%	$H = \frac{\sqrt{3}(G-B)}{2R-G-B}$
Yellow, Magenta, Cyan	95.45%	Y = R + G
Differential	95.45%	RG = (R-G)/(R+G) BD = (B-G)/(B+G) BR = (B-R)/(B+R)
Difference	68.27% 86.64% 86.64%	RG = R-G BG = B-G BR = B-R

The filtering phase uses the threshold values coupled with a complete set of maximum and minimum values to filter every pixel in the image while replacing unusable pixels with black color. Color filtering is done based on original image but the changes are updated on the image resulting from the edge detection.

After the filtering is complete the assumption was made that every pixel in the image that was not black was a portion of a tree trunk. Lines are drawn on longer consecutive segments of edges that remain after the color filtering. These lines are evaluated by their lengths; assuming that each line must be longer than 5 pixels (~135 cm) to be considered as tree trunk but shorter than 15 pixels. The lines are estimated through mean square error optimization.

In the last phase the algorithm tries to pair lines which could represent a tree trunk's both edges. Lines must be close to each other to represent a tree trunk. For each line the algorithm computes relative distance to each other line and adds a pair of lines to the list of trees if relative distance between the lines is less than 10 pixels and they are approximately parallel, based on the following formula:

$$(\text{slope (line1)} / \text{slope (line2)} - 1) < 0.1 \qquad \text{(E. 4)}$$

Once these paired lines are identified, the pairs are connected in the top and bottom to form a polygon. For each tree the algorithm can draw several polygons, because differences in angles, lengths and width. Among all these polygons which represent one tree trunk, the polygons with maximum area and area less than 100 pixels (but more than 36 pixels) are added to the main tree list and all the other polygons are added to a secondary list. If a tree trunk does not contain any other polygons then it is added to main tree list. Tree trunks' diameters are calculated based on the distance between the sidelines of the polygons.

Debris Volume Estimation (Part II). From the trees' diameters, the estimated debris volume is calculated in cubic meters based on the UFST – Debris Volume Estimation Table ((Personal Communication, Dudley Hartel USDA Forest Service, August, 2009). This table contains multipliers for calculating whole trees volume based on the diameter of a tree stem (Table 2), where volumes is about 50% wood and 50% air space.

Table 2. USDA Forest Service Centers for Urban and Interface Forestry's Ground Debris Estimation Table

Tree stem diameter (cm)	Tree debris volume (m^3)
10	0.07
20	0.4
30	1.50
50	5.35
70	15.30
100	38.20
130	76.45
150	114.70

Results

The algorithm was tested on two different Leica ADS40 images. The imagery was taken 2 days after (September 18, 2004) Hurricane Ivan's damage in Pensacola City, FL. The approximate areas of the images were; Image1 - 1860x1816 pixels (Figure 1A), and Image2 - 1347x1866 pixels (Figure 1B). The tool's results, based on 11 collected points, are shown in Figures 2A and 2B.

Figure 2A. Downed tree detection tool results for Image1. Red color was assigned to the main list and green color was assigned to the secondary list.

Figure 2B. Downed tree detection tool results for Image2. Red color was assigned to the main list and green color was assigned to the secondary list.

The downed trees on both images were manually counted as they were observed by visual photo-interpretation. These numbers were used as observed values for testing the tool. Different number of points were collected with the tool for the color threshold phrase to test what number of point are necessary to collect in order to achieve the most accurate and close results compared to the manually counted downed trees (Table 3). Also, estimated total debris volume was calculated (Table 4).

Table 3. Image 1 and Image 2 estimates.

Image1 (1860x1816 pixels)					
	6 points	11 points	17 points	23 points	45 points
Average number of trees found (5 runs)	479.8	648.6	699	686.8	691
Observed trees	622	622	622	622	622
Error	-142.2	26.6	77	64.8	69
Standard Deviation	229.5	58.7	51.9	37.8	40.1
Standard Error	102.6	26.3	23.2	16.9	17.9
Confidence limit	216.0	581.1	639.4	643.3	644.9
	743.6	716.1	758.6	730.3	737.1
Image2 (1347x1866 pixels)					
	6 points	11 points	23 points	34 points	45 points
Average number of trees found (5 runs)	498.4	660.4	687.6	679.8	638.6
Observed trees	610	610	610	610	610
Error	-111.6	50.4	77.6	69.8	28.6
Standard Deviation	143.5	18.5	29.8	38.2	18.9
Standard Error	64.2	8.3	13.3	17.1	8.5
Confidence limit	320.3	637.5	653.4	635.9	616.9
	676.5	683.3	721.8	723.7	660.3

The authors currently do not have existing imagery data and ground debris volume data for the same area to verify debris volume estimation based on actual ground collected data. Thus data in Table 4 is just for informational purposes.

Table 4. Estimated downed tree debris volume (in cubic meters)

Image 1	
Main list	19542
Secondary list	15210
Image 2	
Main list	18107
Secondary list	11419

Limitations

- Shadows created by standing trees can be counted as downed trees.
- Soil variations closely resemble color variations in bark.
- Fences and dirt roads are being counted as trees.

CONCLUSION

The objective was to develop a tool that was rapid but accurate that can help FEMA and USDA estimate downed tree debris volume after a natural disaster. The algorithm revealed an accurate count of downed trees based on the digital images compared to the ground based results. The program converged quickly on a Inter Centrino Duo 2.00 GHz processor and 2GB of RAM on the investigated images (less than 1 minute), while actual post-hurricane debris assessments that accounted for downed trees took several hours and considerable logistical and safety issues in the same area (Duryea et al., 2007; Escobedo et al., 2009). The authors believe that the 12 inch spatial resolution is sufficient to produce accurate diameter values. If the aerial imagery's cost is not prohibitive, the methodology certainly has future application potential.

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REFERENCES

Barnes, C., H. Fritz, J. Yoo, 2007. Hurricane disaster assessments with image-driven data mining, in High-Resolution Satellite Imagery, *GeoRS*(45), No. 6: 1631-1640.

Barni, M., F. Buti, F. Bartolini, and V. Cappellini, 2000. A quasi-Euclidean norm to speed up vector median filtering, *IEEE Transactions on Image Processing*, Vol. 9, No. 10: 1704-1709.

Cheng, F., and A. Venetsanopoulos, 1992. An adaptive morphological filter for image processing, *IEEE Transactions on Image Processing*, Vol. 1, No. 4: 533-539.

Duryea, M.L.E., R. Kampf, C. Littell, and C.D. Rodriguez-Pedraza, 2007. Hurricanes and the urban forest: II. Effects on tropical and subtropical tree species, *Arboriculture and Urban Forestry*, 33: 98-112.

Escobedo, F., C. Luley, J. Bond, C. Staudhammer, and C. Bartel, 2009. A hurricane debris and damage assessment for Florida urban forests, *Arboriculture and Urban Forestry*, 35(2): 100-106.

Gonzalez R., and R. Woods, 1992. *Digital Image Processing*, Addison Wesley, pp 414 - 428.

Gougeon, F., 2000. Towards semi-automatic forest inventories using individual tree crown (ITC) recognition, *Forestry Res. Applications*, Pacific Forestry Centre, Tech. Rep., 2000.

Jenkins, J., D. Chojnacky, L. Heath, and R. Birdsey, 2003. National-scale biomass estimators for United States tree species, *Forest Science*, 49(1): 12-35.

Jenkins, J., D. Chojnacky, L. Heath, and R. Birdsey, 2004. Comprehensive database of diameter-based biomass regressions for North American tree species, *General Technical Report NE-319*, 48 pp, USDA, Forest Service, Delaware, USA.

Key, T., T. Warner, J. McGraw, and M. Fajvan, 2001. A comparison of multispectral and multitemporal information in high spatial resolution imagery for classification of individual tree species in a temperate hardwood forest, *Remote Sensing of Environment*, Volume 75, Issue 1: 100-112.

Lefsky, M., W. Cohen, and T. Spies, 2001. An evaluation of alternate remote sensing products for forest inventory, monitoring, and mapping of Douglas-fir forests in western Oregon, *Canadian Journal of Forest Research*, 31: 78-87.

Magnusson, M., and J. Fransson, 2005. Estimation of forest stem volume using multispectral optical satellite and tree height data in combination, *Scandinavian Journal of Forest Research*, 20: 431-440.

Mallinis, G., N. Koutsias, M. Tsakiri-Strati, and M. Karteris, 2008. Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site, *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 63, Issue 2: 237-250.

Okudaa, T., M. Suzukia, S. Numataa, K. Yoshidaa, S. Nishimuraa, N. Adachib, K. Niiyamac, N. Manokarand, and M. Hashim, 2004. Estimation of aboveground biomass in logged and primary lowland rainforests using 3-D photogrammetric analysis, *Forest Ecology and Management*, 203: 63–75.

Pickens, L., H. Cheshire, and H. Devine. 2000. Use of geographic information systems and photogrammetric techniques to improve the NC division of forest resources pre-suppression fire planning and forest management, in, *Proceedings of the IEEE 2000 International Geoscience and Remote Sensing Symposium*, Vol. VI, Honolulu, Hawaii, 24-28 July 2000: 2712-2714.

Shedd, J., 2005. *Updating Fuel Fire Loads and Vegetation Datasets after a Natural Disaster* [thesis], Raleigh (NC), North Carolina State University.

Soille, P., and M. Pesaresi, 2002. Advances in mathematical morphology applied to geoscience and remote sensing, *Transactions on Geoscience and Remote Sensing*, IEEE, Vol. 40, No.9: 2042-2055.

Sudha, N., S. Nandi, P. Bora, and K. Sridharan, 1998. *Efficient Computation of Euclidian Distance Transform Applications in Image Processing*, IEEE Region 10 International Conference on Global Connectivity in Energy, Computer, Communication and Control. Vol. 1:49 – 52.

Sugumaran, R., M.K. Pavuluri, and D. Zerr, 2003. The use of high-resolution imagery for identification of urban climax forest species using traditional and rule-based classification approach, *Transactions on Geoscience and Remote Sensing*, IEEE, Vol. 41, No.9: 1933-1939.

Weijer, J., T. Gevers, and A. Gijsenij, 2007. Edge-based color constancy, *IEEE Transactions on Image Processing*, Vol. 16, No. 9: 2207-2214.