EXTRACTING TIDAL STREAM NETWORKS FROM HIGH-RESOLUTION REMOTE SENSOR IMAGERY: A PRELIMINARY STUDY

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ABSTRACT:

In this paper we report the results of a pilot project we conduct to develop a semi-automated approach for tidal stream network extraction from remote sensor data. Our test site is part of the North Inlet-Winyah Bay National Estuarine Research Reserve in Georgetown, South Carolina, U.S.A. Largely lower than 1m above sea level, the study site consists of salt marshes behind barrier islands with numerous tidal creeks. The primary data are a high-resolution multispectral image acquired with an Airborne Data Acquisition and Registration (ADAR) 5500 digital camera system in October 2000. Our working procedural route comprises four major components: pattern recognition, spatial modeling, computer vision, and interactive editing. We used pattern recognition to separate stream channels from land, and further processing focused on the stream channels only. We computed a Euclidian distance raster and a Euclidian direction raster by using the channel banks as the source. We used a non-directional filter to extract the strong edges from the Euclidian direction raster. Then, we extracted the initial stream networks (channel centerlines) by selecting the pixels with strong edge values and non-zero distance values that fall within the tidal channels. Finally, we converted the initial raster stream networks into vector polylines for interactive editing with the ADAR image as the reference in a geographic information system (GIS) environment. The result is quite encouraging as virtually all major stream systems and many small streams were successfully extracted. The limitations are mainly with some small streams whose centerlines were not preserved or were broken.

1. INTRODUCTION

Tidal streams are geomorphically and ecologically important (Yang *et al*., 1999; Lohani *et al*. 2006; Torres *et al.* 2006; Fagherazz *et al*. 2008). However, detailed tidal channel network datasets are not readily available for many coastal lowland areas (Fagherazzi *et al*. 1999; Lohani and Mason 2001; Yang 2007).

Stream networks can be mapped through ground surveys or remote sensing. While ground surveys have the potential to provide accurate measurements, they often suffer from serious logistical constraints. With the use of remotely sensed data, stream channels can be delineated by using either manual or automated approaches. The manual approach involves the use of a digitizer and can be quite labor intensive (*e.g.* Heine *et al*. 2004; Novakowski *et al.* 2004); the automated approach is largely based on the use of a digital elevation model (*e.g*. Lin *et al*. 2006) that does not function well in coastal lowlands (Wechsler 2007). Therefore, there is an urgent need to develop effective methods that can help derive detailed hydrographic network datasets for coastal lowlands (Lohani *et al*. 2006).

In this paper we report the results of our pilot project aiming to develop a semi-automated approach for tidal stream network extraction from remote sensor data. Our focus was not to map the area of stream channels but to derive their centerlines. Unlike the area of stream channels, however, stream centerlines cannot be readily extracted from remote sensor imagery. In the following sections, we will briefly describe the study site and the primary data used, and elaborate the working procedural route leading to stream centerline extraction.

2. STUDY SITE AND DATA

Our test site was part of the North Inlet-Winyah Bay National Estuary Research Reserve in Georgetown, South Carolina, U.S.A (Figure 1). With a total area of approximately 7.4 km^2, the study site is largely lower than 1m above sea level (Morris *et al.* 2005; Yang 2007). It features the salt marshes dominated by the smooth cordgrass (*Spartina alterniflora*) and numerous ocean controlled tidal creeks (Figure 2).

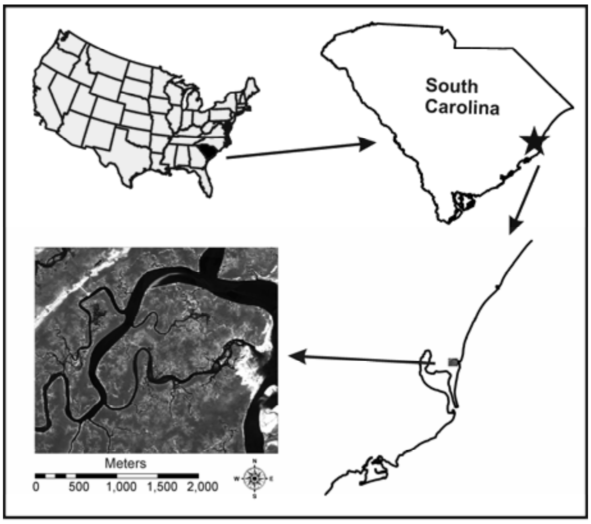

Figure 1. Location of the study area.

The primary data were an image acquired by using an Airborne Data Acquisition and Registration (ADAR) 5500 digital camera system in October 2000. The ADAR image has a nominal spatial resolution of 0.7 meter and consists of four spectral bands: blue (450-540 nm), green (520-605 nm), red (610-690 nm), and near infrared (750-860 nm).

Two other types of data were also collected: (1): Stream networks from the High-Resolution National Hydrographic Dataset (NHD) created by the United States Geological Survey (USGS). The stream lines were originally derived from USGS 1:24,000 topographic maps published in 1973. While most of the large creeks are present, many small ones are absent when using the ADAR image as the reference (Figure 3); (2): A mosaic of the 2006 Digital Orthophoto Quarter Quadrangle (DOQQ) color infrared image. Because of its geometric integrity, the DOQQ mosaic will be used as a reference to georectify the ADAR image.

Figure 2. Photography showing part of the study site. Note that the salt marshes are dominated by a single species of the smooth cordgrass (*Spartina alterniflora*) (Photographed by Luoheng Han on 13 August 2003).

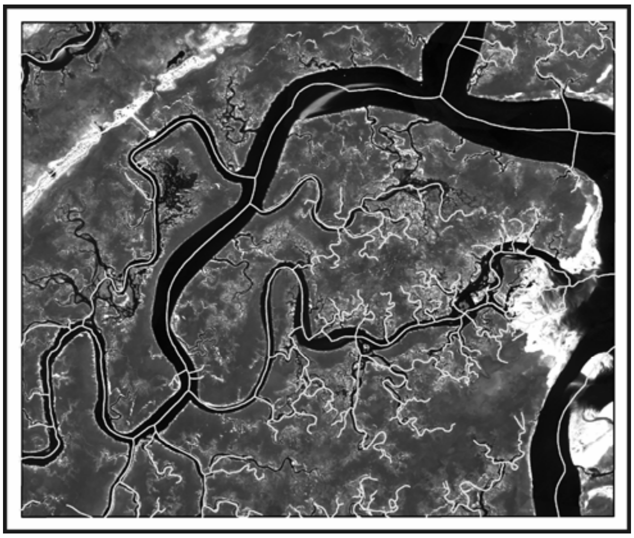

Figure 3. Overlaying of the NHD stream lines (in white) with the near infrared band (streams in black) of the ADAR image. While most of the large creeks are present, some other large ones and many small ones are absent. The image dimension is approximately 2953 m by 2491 m.

3. TIDAL CREEK NETWORK EXTRACTION

The method we developed for tidal stream network extraction comprised four major components: pattern recognition, spatial modeling, computer vision, and interactive editing (Figure 4). Each component had its major purpose(s) and comprised one or more sub-components. The following paragraphs document the details for each component.

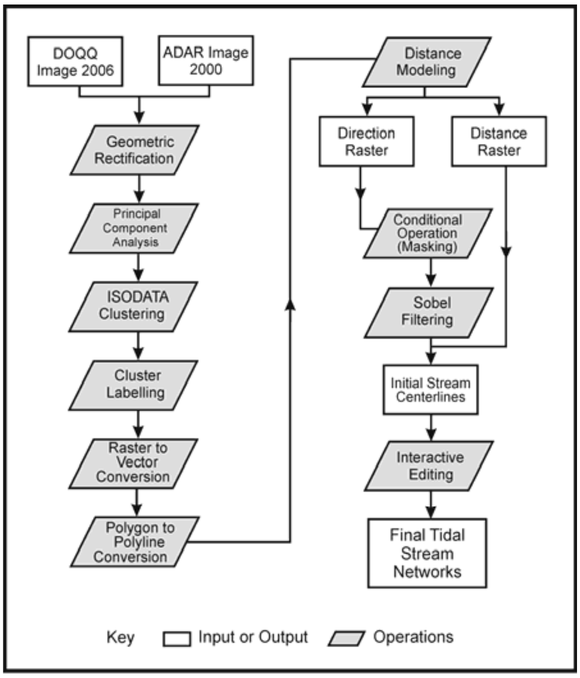

Figure 4. Flowchart of the working procedural route. Please refer to the text for some more specific operations since this chart only illustrates the major ones.

3.1 IMAGE CLASSIFICATION

The purpose of this component was to separate the tidal streams from other areas. This part of work had four sub-components: geometric correction, principal component analysis, unsupervised classification, and post-classification processing.

3.1.1 Geometric Correction: The radiometric quality of the ADAR image is quite good but the geometric distortion introduced by airborne remote sensing needs to be rectified. This is necessary for correctly planimetric mapping of tidal channels. Using the 2006 DOQQ mosaic as the reference, an image-to-image correction was performed through a second-degree polynomial transformation function and the nearest neighborhood resampling method. The raw ADAR image was rectified to the Universal Mercator Projection (UTM) map space (N16 zone), the WGS1984 horizontal datum, and the WGS1984 ellipsoid.

3.1.2 Principal Component Analysis (PCA): Implementing PCA here was not merely for data dimension reduction but for image noise suppression. Image noise needs to be suppressed before actually classifying the ADAR image. The PCA was applied to transform the original ADAR data into four uncorrelated principal components. The first three components explain a total of 99.47% of the variance present in the entire ADAR dataset. The fourth component accounts for 0.53% of the variance and contains much image noise, and thus was excluded for further analysis.

3.1.3 Unsupervised Classification: The ISODATA (Iterative Self-Organizing Data Analysis Technique) algorithm was used to identify spectral clusters from the first three principal components of the ADAR image (Figure 4A). Of all the clustering parameters, the number of spectral classes is the most critical (Booth and Oldfield 1989; Jensen 2005). Although the end product of image classification comprised only two information classes, namely, channels and other land areas, sixty spectral clusters were used in order to accommodate a variety of tidal channels that are different in dimension and physical conditions. Two other important parameters include the convergence value that was specified as 0.990 and the maximum number of iterations that was assigned as 60. The resulting 60 spectral clusters (Figure 4B) were carefully interpreted through visual inspection of the original ADAR image, and were labeled as either channels or other land areas.

3.1.4 Post-classification Processing: A careful examination of the initial channel map produced using the unsupervised classification found some misclassification errors occurring at the water-land boundaries. A standard 5X5 majority filter was applied to the initial channel map for boundary error suppression. The resulting map comprises channels (23.79%) and non-channels (76.21%) (Figure 4C).

3.2 DISTANCE MODELING

The channel map produced by image classification (see Section 3.1) provides the information concerning the area of stream channels in the study site. Two additional major operations were applied to help extract the stream centerlines from the channel map: distance modeling and non-directional filtering. This section details the distance modeling component that was actually based on the Euclidean (or straight-line) distance analysis.

3.2.1 Preparation of the Source: The source specifies the location of the objects of interest, namely, the channel banks for the current study. In order to prepare the source, the channel map was converted from raster into polygon features. A total of 1248 polygons were formed to represent the channels. Then, the channel polygons were further converted into 1652 polylines (Figure 4D). These polylines actually represent the stream banks. Note that converting the channel raster directly into polyline features is possible but would include not only the stream banks but also many other unwanted features.

3.2.2 Euclidian Distance and Direction: With the channel bank polylines as the source, both Euclidian distance and direction were computed. The distance output raster contains the measured straight-line distance, in meters, from every cell to the nearest channel banks (Figure 4E); the direction output raster contains the azimuth direction, in degree, from each cell to the nearest banks (Figure 4F).

3.3 NON-DIRECTIONAL FILTERING

The purpose here was to select the pixels with strong gradient (*i.e.* edges) that are present in the Euclidian direction raster. In doing so, a conditional operator was applied to mask the direction raster with the channel area map produced by image classification (Figure 4C) since we were only interested in the channel area. The masked direction raster is shown in Figure 4G.

Then, the Sober operator was applied to the masked direction raster for computing an approximation of the gradient of the image intensity at each cell (Duda and Hart 1973). The result of the Sober operator is a 2-dimensional map of the gradient at each cell (Figure 4H).

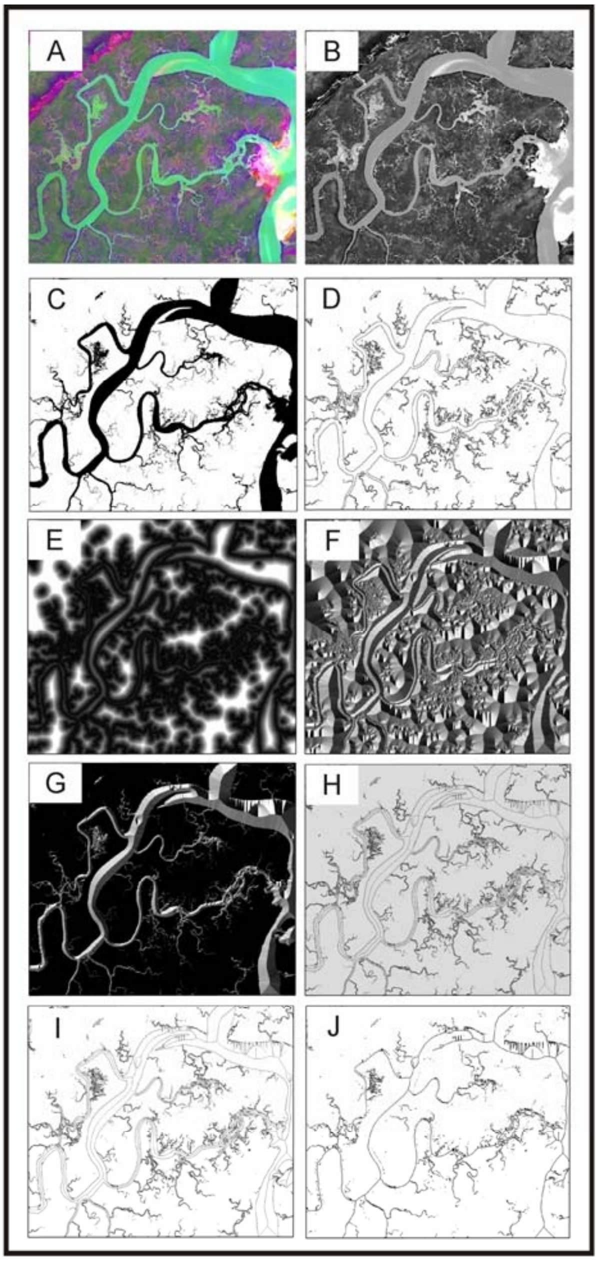

Figure 5. Sequential (major) procedures used in tidal stream network extraction. A: Color composite of the first three principal components from the ADAR imagery; B. Spectral clusters identified by the ISODATA algorithm; C: Tidal channels (raster); D: Tidal channels (polylines); E: Euclidian distance output raster from D; F: Euclidian direction output raster from D; G: Masked direction raster; H: Non-directional gradient magnitude for each cell after the Sobel filtering of G; I: Selected edges after applying a threshold to H; J: Initial tidal stream networks after selecting the pixels with strong gradient magnitude and non-zero distance values.

Finally, by using the original ADAR image as the reference a threshold value was interactively determined to help identify the pixels with high gradient magnitudes that are either channel banks or centerlines. By using the threshold value, the output raster from the Sober operator was reduced to a binary map with edges and non-edges only (Figure 4I).

3.4 INITIANL CENTERLINE EXTRACTION AND INTERACTIVE EDITING

Since the above binary map contains both channel banks and centerlines, a conditional operator was further applied to select the centerlines that are actually the edge pixels with non-zero distance values in the Euclidian distance output raster (Figure 4E). The selected channel centerlines form the initial stream networks (Figure 4J).

To further improve the accuracy of channel centerline mapping, the initial stream networks were converted from raster to polyline features for interactive editing in a GIS environment. This was done by using the original ADAR image as the reference.

Although a quantitative accuracy assessment is still under way, our visual inspection has confirmed that virtually all large streams and many small streams have been successfully extracted; the limitations are mainly with some small streams whose centerlines are not preserved or broken.

4. CONCLUSIONS

We have developed a semi-automated method for tidal stream network extraction from high-resolution remote sensor imagery. Our method comprises four major components: pattern recognition, spatial modeling, computer vision, and interactive editing. Pattern recognition is for identifying tidal streams from remote sensor imagery, and the three additional working components target the extracted tidal streams only. The Euclidian distance and direction modeling helps enhance the gradient magnitude along the stream centerlines; non-directional filtering aims to identify strong edges that are the initial stream centerlines. Finally, GIS-based interactive editing intends to further improve the accuracy of the initial stream networks.

This method is quite fast, and can potentially save much labor that would be formidable for a manual digitizing approach, particularly over a large area. The high-resolution imagery used in this method are widely available as the DOQQ data in the United States; and most of the operators needed are readily available from some major commercial GIS or image processing systems.

We applied this method to a coastal marsh area, and the initial result is quite encouraging as virtually all major streams and many small streams have been successfully predicted. The limitations are mainly with some small streams whose centerlines are not preserved or broken. Further work is needed to improve the accuracy of channel classification and to adopt a more robust non-directional filter that can potentially preserve edges that are small in dimension.

REFERENCES

Duda,R. and Hart,P., 1973. *Pattern Classification and Scene Analysis*. John Wiley and Sons, pp.271-2.

Fagherazzi, S., Bortoluzzi, A., Dietrich, W.E., Adami, A., Lanzoni, S., Marani, M. and Rinaldo, A., 1999, Tidal networks 1. Automatic network extraction and preliminary scaling features from digital terrain maps. *Water Resources Research*, 35, pp. 3891-3904.

Fagherazzi, S., Hannion, M. and D'Odorico, P., 2008. Geomorphic structure of tidal hydrodynamics in salt marsh creeks. *Water Resources Research*, 44(2), pp.W02419.

Heine, R.A., Lant, C.L. and Sengupta, R.R., 2004. Development and comparison of approaches for automated mapping of stream channel networks. *Annals of the Association of American Geographers*, 94 (3), pp. 477-490.

Jensen, J. R., 2005. *An Introductory Digital Image Processing: A Remote Sensing Perspective* (3rd). Prentice Hall, New Jersey, pp. 296-301.

Lin, W.T., Chou, W.C., Lin, C.Y., Huang, P.H. and Tsai, J.S., 2006, Automated suitable drainage network extraction from digital elevation models in Taiwan's upstream watersheds. *Hydrological Processes*, 20 (2), pp. 289-306.

Lohani, B. and Mason, D.C., 2001, Application of airborne scanning laser altimetry to the study of tidal channel geomorphology. *ISPRS Journal of Photogrammetry and Remote Sensing*, 56 (2), pp. 100-120.

Lohani, B., Mason, D.C., Scott, T.R. and Sreenivas, B., 2006. Extraction of tidal channel networks from aerial photographs alone and combined with laser altimetry. *International Journal of Remote Sensing*, 27(1), pp.5-25.

Morris, J.T., Porter, D., Neet, M., Noble, P.A., Schmidt, L., Lapine, L.A. and Jensen, J., 2005. Integrating LIDAR, multispectral imagery and neural network modeling for marsh classification. *International Journal of Remote Sensing*, 26 (23), pp. 5221-5234.

Novakowski, K.I., Torres, R., Gardner, L.R. and Voulgaris, G., 2004. Geomorphic analysis of tidal creek networks. *Water Resources Research*, 40 (5), pp. W05401.

Torres, R., Fagherazzi, S., vanProosdij, D. and Hopkinson, C., 2006. Salt marsh geomorphology: Physical and ecological effects on landform. *Estuarine, Coastal and Shelf Science*, 69(3-4), pp.309-310.

Tou, J. T., and Gonzalez, R. C., 1974. *Pattern Recognition Principles.* Reading, Massachusetts: Addison-Wesley Publishing Company, 377 pp.

Wechsler, S.P., 2007, Uncertainties associated with digital elevation models for hydrologic applications: a review. *Hydrology and Earth System Sciences*, 11 (4), pp. 1481-1500.

Yang, X., 2007. Using lidar and high-resolution remote sensor data for topographic mapping in a coastal marsh area: a preliminary study. In: *Proceedings of the 23rd International Cartographic Conference*, Moscow, Russia.

Yang, X., Damen, M. C. J., and Zuidam, van, R., 1999. Satellite remote sensing and GIS for the analysis of channel migration changes in the active Yellow River delta. *International Journal of Applied Earth Observation and Geoinformation*, 1(2), pp.146-157.

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