Classification of Channel Bifurcation Points in Satellite Images of River Deltas

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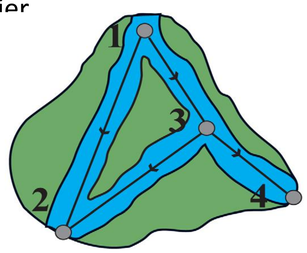
Motivation

River deltas are very important landforms that are both home to about **500 million people** and some of the most **complex ecosystems** on Earth. Over long time scales they also form high-quality reservoirs for **hydrocarbons, groundwater flow and potential CO_2 storage**. Supply of sediments and nutrients has become increasingly vulnerable under anthropogenic influence, e.g. because of sea level rise and dam construction. Numerical descriptions of deltaic flow properties and risk analysis through **graph theory** is an old idea that has been getting a lot of attention again with the advent of remote sensing imagery [1]. Many deltas are very complex and an **automated node detection method** would make the analysis significantly faster and easier.



$$D^{\text{in}} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Figure 1: Several graph matrices can be coomputed for this small river network, e.g. adjacency *A*, direction *D* and Laplacian *L*

Data and Features

The Google Earth Engine API provides access to large datasets of **satellite imagery** such as from the Landsat and Copernicus programs. 60 images of large deltas of differing size and complexity were extracted and 560 points were (tediously!) manually labeled as bifurcation points (as well as 1400 normal points). River channel pixels were identified using a singularity analysis method [2], which also permits computing centerlines and expected flow directions.

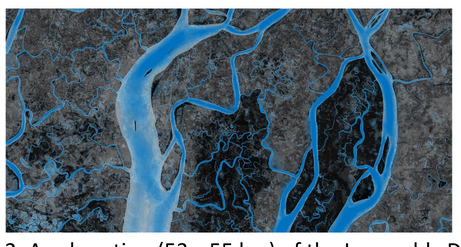


Figure 2: A subsection (53 x 55 km) of the Irrawaddy Delta in South-East Asia with expected flow vectors.

Features that are computed in the small region around each point: The number of connected components, channel width distributions, flow direction distributions, number of objects that reach the edges, ratio of smallest/largest velocities etc.

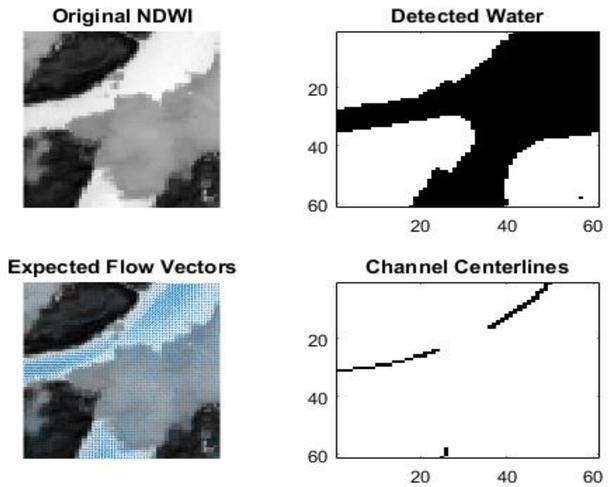


Figure 3: Example features in the local region around a channel bifurcation point.

Classification Methods

Two main approaches were used:

- Classification based directly on the images using **GIST** and **HOG** (histogram of oriented gradients) [3] feature descriptors. Using **convolutional neural networks** was ruled out because of the limited size of the dataset.
- **Feature extraction** in combination with standard classifiers such as **kernel SVM, GDA , multinomial logistic regression and boosted decision trees**.

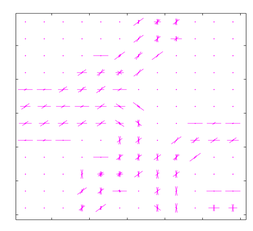


Figure 4: Visualization of HOG features for the channel bifurcation point shown in figure 3.

	Kernel SVM		AdaBoostM1		HOG	
Truth	**0.955**	0.045	**0.944**	0.137	**0.907**	0.286
	0.155	**0.845**	0.074	**0.818**	0.093	**0.714**

Figure 5: Confusion matrices. Class 0 corresponds to 'no bifurcation point', so **false positives are bad** since there are many more regular points than bifurcation points!

Results

- **Kernel SVM** with extracted features gave the best mean error (**7.5%**) and gave the **lowest false positive rate**
- HOG worked surprisingly well given the large variety of bifurcation points
- GDA, logistic regression and GIST worked poorly.

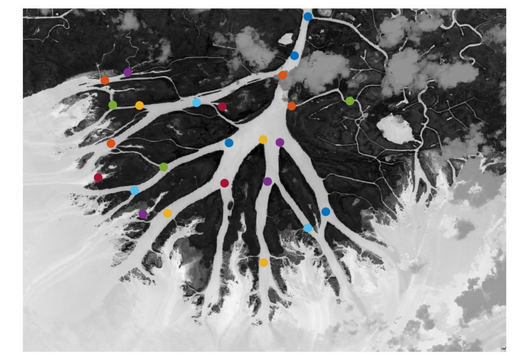


Figure 5: Application of kernel SVM classifier on the Wax Lake Delta

Summary and Future Research

- Hard part: getting the data, manually labeling a large number of points and finding useful features. Once the data is in the form of rows and columns of observations, classification is relatively straightforward.
- Applying the method to a large number of deltas to compute spatial statistics is the next step in my research.

Bibliography

[1] A. Tejedor, 'A graph-theoretic approach for studying connectivity and steady state transport on deltaic surfaces', AGU Water Resources Research, Vol. 51, pp. 3998-4018, 2015

[2] F. Isikdogan, A.C. Bovik, and P. Passalacqua, "Automatic channel network extraction from remotely sensed images by singularity analysis," *IEEE Geoscience and Remote Sensing Letters*, 12, 11, 2218-2221, 2015

[3] Dalal, N. and B. Triggs. "Histograms of Oriented Gradients for Human Detection", *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Vol. 1 (June 2005), pp. 886–893.