Water detection in an image using HOG and Neural Networks

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Overview

Our project is to make software capable of determining where water lies in an image. These locations will then be used to determine heights of water for rivers and other bodies of water. Current processes are expensive. The proposed method will be cheaper and easier to implement and maintain.

Our method for determining where water is, uses an automated approach with supervised validation of the results. We read in training images, process their data, and using machine learning to classify where water is in an image. The process breaks down into three phases: *Pre-processing, Feature Extraction,* and *Classification*. **Pre-processing** is modifying the input images to be able to extract meaningful data from them. **Feature Extraction** takes the preprocessed images and retrieves the pertinent data that identifies water vs. non-water. **Classification** uses a Neural Network algorithm that takes in the extracted features and determines what is water or not water in an image.

Pre-processing

To perform unsupervised extraction of features, the source image must be first analyzed to determine section of an image that are most likely to be water.

1. All Images are blurred using a low pass temporal filter.
2. Used K-means to group similar colors together into bands used as labels.

Feature Extraction

3. The input image is split into smaller regions.
4. Each smaller region has features extracted using Gabor filters [1]

Regions that fall between 2 bands generated from the preprocessing are not used as data.

Classification

5. Train the Neural Network on the data.
6. Validate and test predictions from trained Neural Network.

1. Low Pass Temporal Filter

2. Bands from K-Means

3. Input Image

4. Gabor Filter Generation

6. Classified Image

Conclusion

Originally we had poor results using a different feature vector called HOG[2]. This produced poor and almost random looking results. Switching to the Gabor filter led to failure accurate results. We had a low rate of misidentifying non-water as water, however confusing artifacts of the image such as reflections on the water caused a higher rate of the converse prediction (misclassifying water as non-water).

Being able to detect water in an image initially looked to be a simpler problem than it was. Numerous issues arose depending on the environmental conditions. Examples of issues are lighting, wind, fog, season (snow), and obstructions (boats/people). More advanced technology might be required to handle these outliers.

Sources

[1] Farshad Nourbakhsh, P.B.Pati and A.G.Ramakrishnan, "Text Localization and Extraction from Complex Gray Images," *Proc. Indian Conf. Vision, Graphics Image Processing, ICVGIP 2006*, Dec. 13-16, 2006, pp. 776-785.
[2] Dalal, N. and Triggs, B., "Histograms of Oriented Gradients for Human Detection," IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2005, San Diego, CA, USA
[3] Dr. Cenek. Expertise and direction.