Team Indentation Error Final Project

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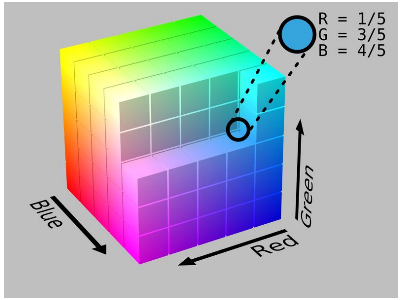
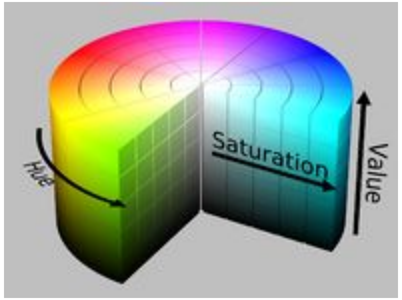
System Outline

- Pre-processing
- Feature Extraction
- Classification
- Post-processing
- Summary

Pre-processing: Color Spaces



- RGB - given, intuitive
- HSV - performed well in preliminary analysis
- GRY - intuitive, emphasis on intensity (technically redundant*)
  - GRY = .2989*R + .5870*G + .1140*B



Pre-processing: Bilateral Filter

$$I^{\text{filtered}}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

$$W_p = \sum_{x_i \in \Omega} f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

I^{filtered} is the filtered image;

I is the original input image to be filtered;

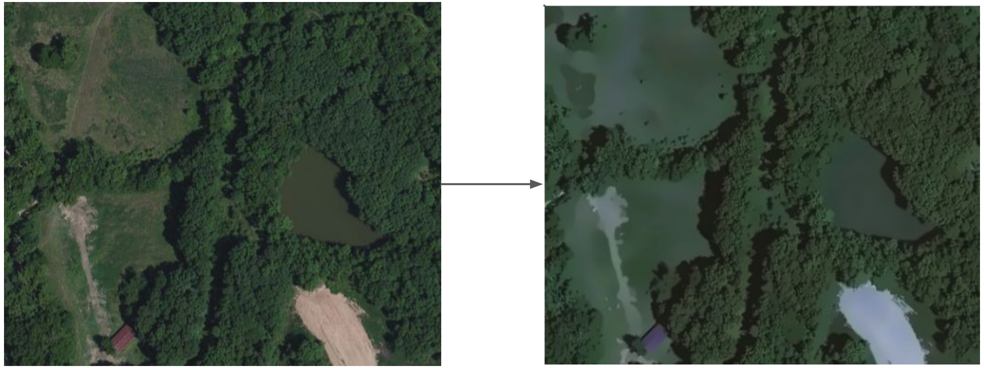
x are the coordinates of the current pixel to be filtered;

Ω is the window centered in x;

Effectively smooths texture while preserving edge boundaries better than a standard Gaussian.

Pre-processing: Non-Local μ Denoising

- "Semi-local" filter designed to remove Gaussian noise from images
- Performs a more distant search for "similar" pixels to average in
- Performs particularly well smoothing ponds and fields



Pre-processing: Canny Edges

1. **Intensity Gradient:** convolve with X and its transpose:

$$\begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix}$$

$$\mathbf{G} = \sqrt{\mathbf{G}_x{}^2 + \mathbf{G}_y{}^2}$$

$$\mathbf{\Theta} = \operatorname{atan2}(\mathbf{G}_y, \mathbf{G}_x)$$

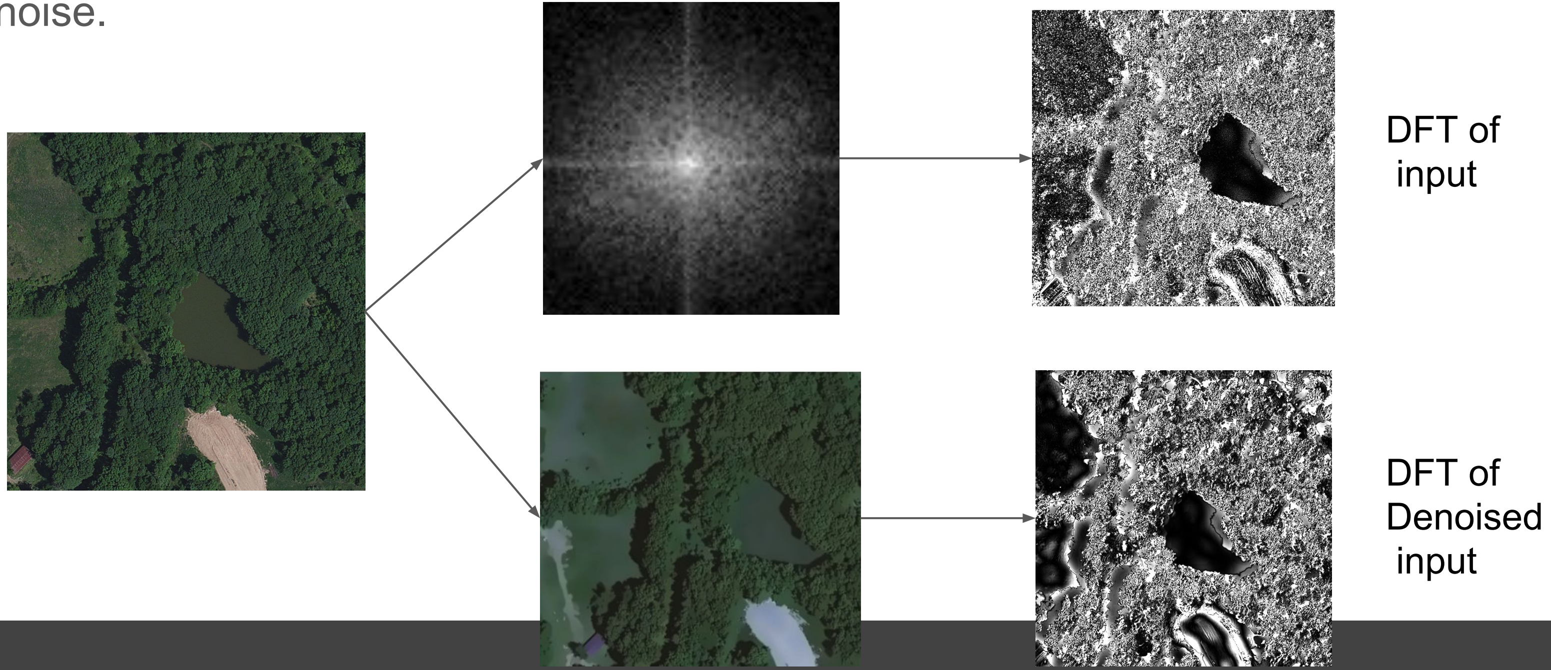
*rounded to nearest axis/main-diagonal

2. **Non-Max Suppression:** compare neighboring intensity gradient magnitudes and force outlying values further toward extremes

3. **Threshold:** cut off high and low values for the most probable and improbable edges

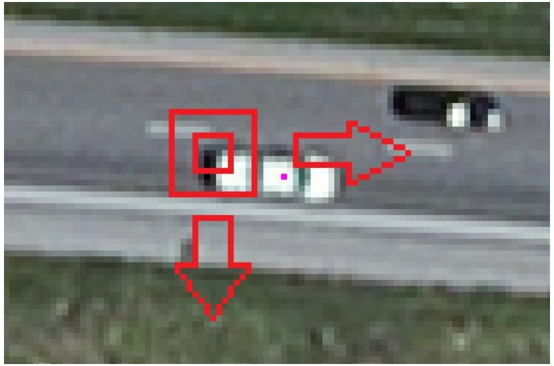
Pre-processing: Fourier Transform

- Transform a grayscale image to 2D frequency domain with a DFT, masking the low frequency components, revert back to image with IDFT with reduced low frequency noise.



Feature Extraction: Histograms

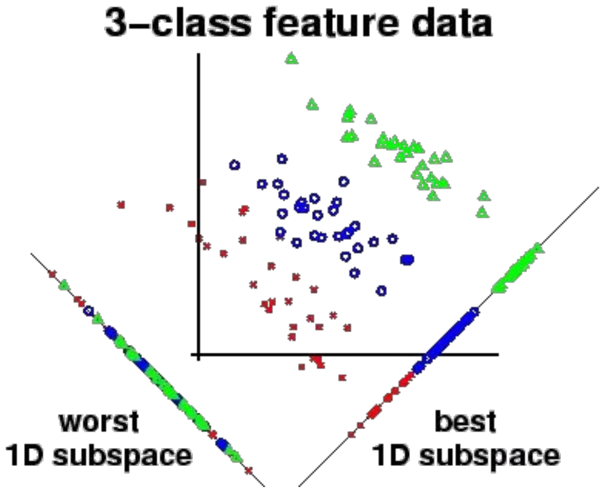
- Sliding window histogram aggregation
- Why not make each pixel a feature?
  - Higher dimensionality
  - Higher variability (aggregation is invariant)
- Append center values to preserve focus
- Loss of precision due to memory
  - data type linear range mapping
  - binning for histograms
- Major computational bottleneck



Classification: LDA

Motivation:

- The problem at hand involves the classification of multiple classes (LDA is generally considered the goto)
- Believed it was safe to assume unimodal Gaussian likelihood within label classes (consistent and characteristic targets)
- Limited training set which would make training models like neural networks more difficult
- Considers within class and between class variance



LDA: Cont.

Implementation:

- Assigned a class to each pixel in image (Red Car, White Car, Pool, Pond, and **Background**).
- Background accounts for more than 99.3% of pixels. In order to avoid over training on background, only 0.7% was included in model fitting
- Accomplished via minimizing within class variance (**Sw**) and maximizing between class separability (**Sb**) according to the objective function:

$$(12) J(\mathbf{w}) = \frac{(\mathbf{m}_2 - \mathbf{m}_1)(\mathbf{m}_2 - \mathbf{m}_1)^T}{s_1^2 + s_2^2} = \frac{\mathbf{w}^T \mathbf{S}_B \mathbf{w}}{\mathbf{w}^T \mathbf{S}_W \mathbf{w}}$$

LDA: Cont.

- The objective function is then minimized by differentiating with respect to weights:

$$\frac{\partial J(\mathbf{w})}{\partial \mathbf{w}} = 0$$

- This results in the weight update equation: $\mathbf{w}^* = \mathbf{S}_W^{-1}(\mathbf{m}_2 - \mathbf{m}_1)$
  - Where:

$$\mathbf{m}_1 = \frac{1}{N_1}\sum_{n \in C_1} \mathbf{x}_n, \quad \mathbf{m}_2 = \frac{1}{N_2}\sum_{n \in C_2} \mathbf{x}_n$$

  - And: Sw^(-1)= inverted within class variance matrix

Post-processing: Center of Contour

Problem: Needed a mapping of pixel label probabilities to discrete centers

Accomplished with the help of OpenCV

1. Convert image to grayscale
2. Gaussian smooth using a 5x5 kernel
3. Apply a binary threshold (255 = 1, 60 or lower = 0)
4. Calculate closed area contours via border following*
5. Calculate each shape's image moment according to: $M_{ij} = \sum_x \sum_y x^i y^j I(x, y)$
   a. (i, j) = moment order
6. Calculate x and y centroids according to: $C_x = \frac{M_{10}}{M_{00}}$ and $C_y = \frac{M_{01}}{M_{00}}$

**Topological Structural Analysis of Digitized Binary Images by Border Following SATOSHI SUZUKI*

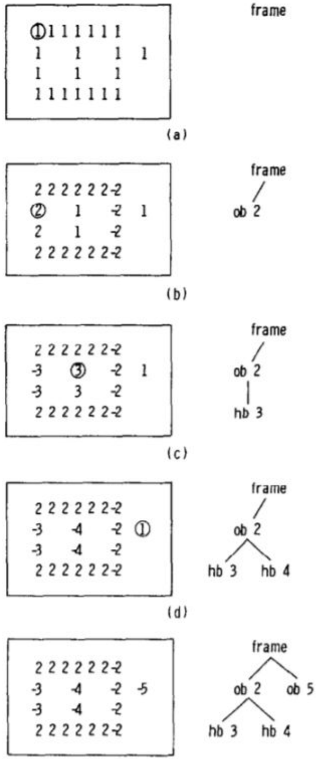
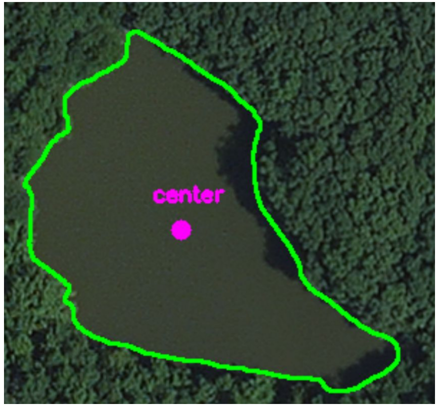


Figure depicting border following algorithm

Center of Contour: Cont.

Results on prelabeled data:

- Green outline depicts recognized contour
- Purple dot depicts centroid of pixel level contour
- Black and white images depict binary label input



Summary

Future considerations include:

- Labeling additional classes to reduce variability of the background class
- Supplementing the edge/gradient features in preprocessing
- Application of other classifiers and ensembling
- Implement area/perimeter features

The End