Canonical Correlations for Detection and Classification of Underwater Objects from Sonar Imagery

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Introduction $\mathbf{x}$ $\mathbf{y}$

CCA Review K

Detection Results H_0 H_1

Classification Results $\hat{\mathbf{x}}$

Concluding Remarks

Problem Statement & Motivations

Detection and classification of underwater targets from sonar imagery is complicated due to various factors such as variations in operating and environmental conditions, competing man-made and natural clutter, variations in target shapes, compositions and orientation.

Motivations:

- ✓ In a real environment, the decision about the presence and type of an object is usually made based on the properties of the target signature such as highlight and shadow structures.
- ✓ For detection purposes, detector should discover a measure to distinguish between the hypothesis of noise only or the hypothesis of signal plus noise
- ✓ For classification purposes, the feature extraction process should discover a small set of features that
  - ✓ carries discriminatory target/non-target information.
  - ✓ remains robust to environmental and operating variations.

Proposed Method

Idea: The presence of a target yields similar coherence measures between columns in an Region of Interest (ROI) and these coherence patterns are different than those of the non-target objects yielding a method for detection and classification.

Why Canonical Correlations?

✓ Coherence analysis between two data channels can easily be performed by mapping the data to their canonical coordinates and using the canonical correlations. Canonical correlation analysis (CCA) can be used to

- implement the optimum Neyman-Pearson detector
- Provide an elegant framework for feature extraction and classification
- Provide the right coordinate system for analysis of coherence between two data channels
- Coherence between columns is higher for an ROI over a target then over a background

✓ Canonical correlations extracted from ROI's are used for ***both*** detection and classification

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Canonical Coordinate Analysis - An Overview

Two-channel data: $\mathbf{x} \in \mathbb{R}^{m\times 1}$ and $\mathbf{y} \in \mathbb{R}^{n\times 1}$

Composite covariance matrix: $$E\left[\begin{pmatrix}\mathbf{x}\\ \mathbf{y}\end{pmatrix}\begin{pmatrix}\mathbf{x}^H & \mathbf{y}^H\end{pmatrix}\right] = \begin{bmatrix} R_{xx} & R_{xy} \\ R_{yx} & R_{yy}\end{bmatrix}$$

SVD of the Coherence Matrix $$C = R_{xx}^{-1/2} R_{xy} R_{yy}^{-H/2} = FKG^H \quad \text{and} \quad F^H C G = K,$$ $$F^H F = I, \;\; G^H G = I, \qquad K = \text{diag}[k_1, k_2, \ldots, k_m];$$

$\mathbf{u}$: Canonical coordinates of $\mathbf{x}$

$\mathbf{v}$: Canonical coordinates of $\mathbf{y}$

$$\begin{bmatrix}\mathbf{u}\\ \mathbf{v}\end{bmatrix} = \begin{bmatrix} F^H & 0 \\ 0 & G^H\end{bmatrix}\begin{bmatrix} R_{xx}^{-1/2} & 0 \\ 0 & R_{yy}^{-1/2}\end{bmatrix}\begin{bmatrix}\mathbf{x}\\ \mathbf{y}\end{bmatrix}$$

Composite covariance matrix of $\mathbf{u}$ and $\mathbf{v}$:

$$E\left[\begin{pmatrix}\mathbf{u}\\ \mathbf{v}\end{pmatrix}\begin{pmatrix}\mathbf{u}^H & \mathbf{v}^H\end{pmatrix}\right] = \begin{bmatrix} R_{uu} & R_{uv} \\ R_{vu} & R_{vv}\end{bmatrix} = \begin{bmatrix} I & K \\ K & I\end{bmatrix},$$

The diagonal matrix K is the canonical correlation matrix of canonical correlations $k_i, i = 1:m$

The top N diagonal elements of K (arranged in descending order) are used as features.

CCA-Based Detection

Implements the Neyman-Pearson detector for testing between $H_0 : \mathbf{y} : CN_n[0, R_{nn}]$ i.e. noise alone versus $H_1 : \mathbf{y} : CN_n[0, R_{yy} = R_{xx} + R_{nn}]$ i.e. signal plus noise

The log-likelihood in CCA

$$\begin{aligned} l(\mathbf{y}) &= (R_{yy}^{-1/2}\mathbf{y})^H (I - CC^H)(R_{yy}^{-1/2}\mathbf{y}) \\ &= (G^H R_{yy}^{-1/2}\mathbf{y})^H (I - KK^H)(G^H R_{yy}^{-1/2}\mathbf{y}). \end{aligned}$$

Which can be rewritten as

$$l(\mathbf{y}) = \sum_{i=1}^{n} |g_i^H R_{yy}^{-1/2}\mathbf{y}|^2 \left(\frac{k_i^2}{1 - k_i^2} \right)$$

leads to J-divergence (Pezeshki and Scharf 2006) test between H_0 and H_1

$$J = E_{H_1} l(\mathbf{y}) - E_{H_0} l(\mathbf{y}) = tr(CC^H + (CC^H)^{-1} - 2I) = tr(KK^H + (KK^H)^{-1} - 2I)$$

$$J = \sum_{i=1}^{m^2} (k_i - \frac{1}{k_i})^2$$

i.e. the rank-r detector that maximizes J-divergence uses the *dominant* canonical correlations

CCA-Based Feature Extraction (Estimation Framework)

Optimal rank- $r \leq n$ Wiener filter estimate of channel $\mathbf{x}$ (signal) from channel $\mathbf{y}$ (observation) can be generated in CCA-domain

$$\hat{\mathbf{x}} = R_{xx}^{-1/2} F K G^H R_{yy}^{-1/2} \mathbf{y}$$

The minimum error covariance and volume of error concentration ellipse

$$Q_{xx} = R_{xx}^{-1/2} F(I - K^2) F^H R_{xx}^{H/2}. \qquad V = \frac{\det(Q_{xx})}{\det(R_{xx})} = \det(I - K^2).$$

With Processing Gain and Information Rate

$$PG = V^{-1} \qquad R = -(1/2)\log V$$

Clearly the *dominant* canonical correlations are the ones that minimize V, maximize PG and R

CCA-Based Feature Extraction (con't)

The rank- r estimator can be written as

$$\hat{\mathbf{x}} = R_{xx}^{-1/2} F K_r G^H R_{yy}^{-1/2} \mathbf{y}$$

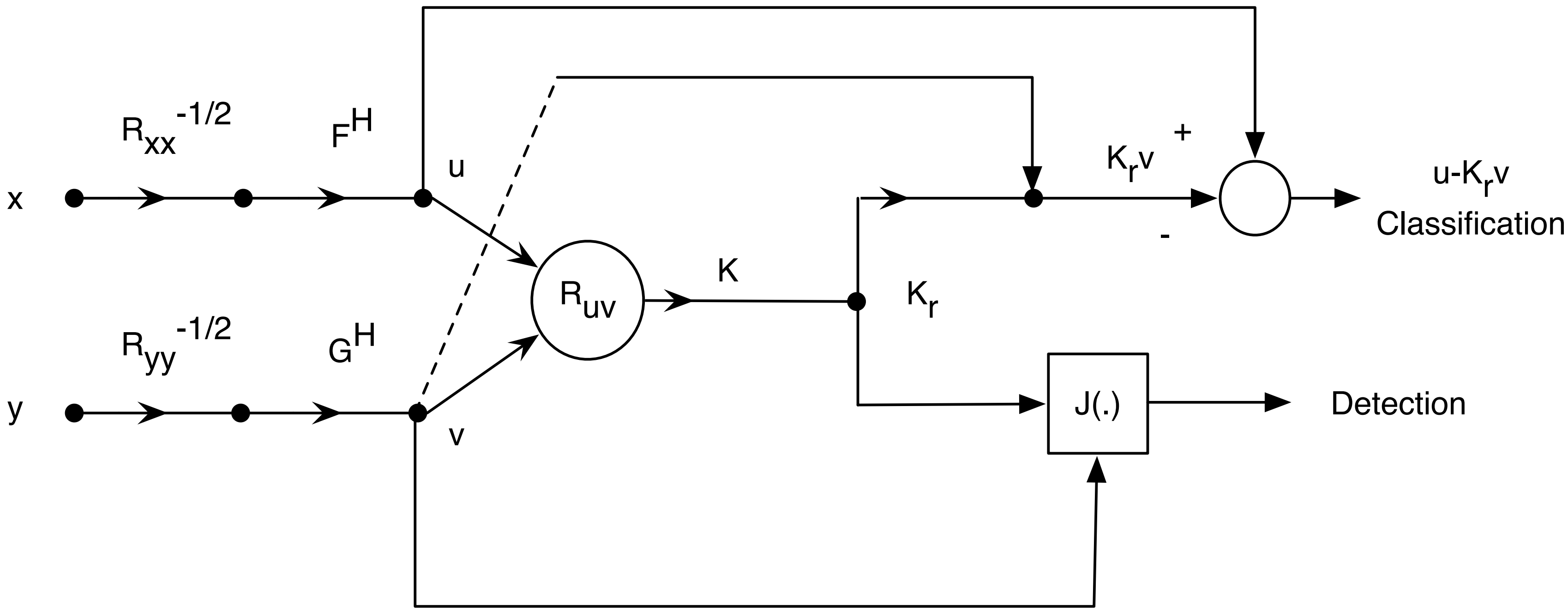
and in canonical coordinates

$$\hat{\mathbf{u}} = K_r \mathbf{v}$$

✓ Thus, dominant correlations that carry most coherent information allow for estimating one channel from the other one. Clearly, targets are more coherent than the environment in which it is found.

✓ Dominant Canonical correlations or the estimation residual $\mathbf{u} - K_r \mathbf{v}$ can be used as features for classification.

CCA-Based Detection and Classification



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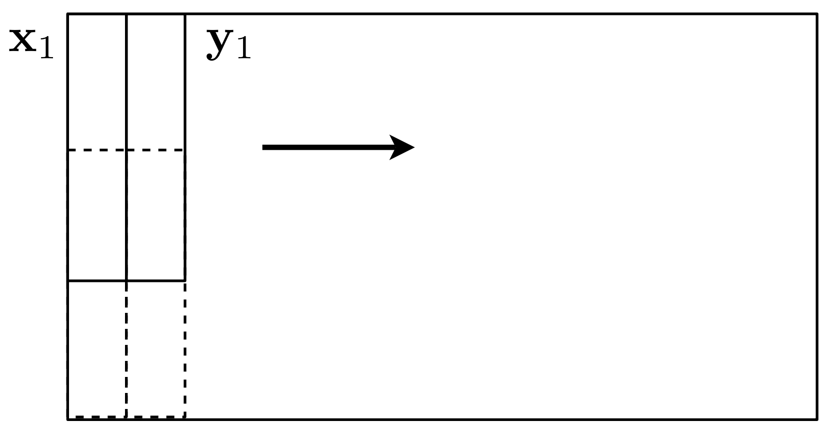
Pre-Processing and Feature Extraction

- ✓ Serpentine Forward-Backward Filter Normalization (Dobeck, SPIE 2005) was first applied to reduce the variability of the local mean and enhance target shadow and highlight.
- ✓ After normalization, the first 120 pixels corresponding to the sonar altitude, which corresponds to 1/10th of the range were discarded.
- ✓ Each image was then partitioned into M x N Regions of Interest (ROI) of size 12 x 34 which were experimentally determined based on average target size.
- ✓ 50% overlapping to avoid splitting of target amongst ROI's.
- ✓ Each ROI is then channelized column-wise (8-dimensional) with 7 pixel channel overlap.

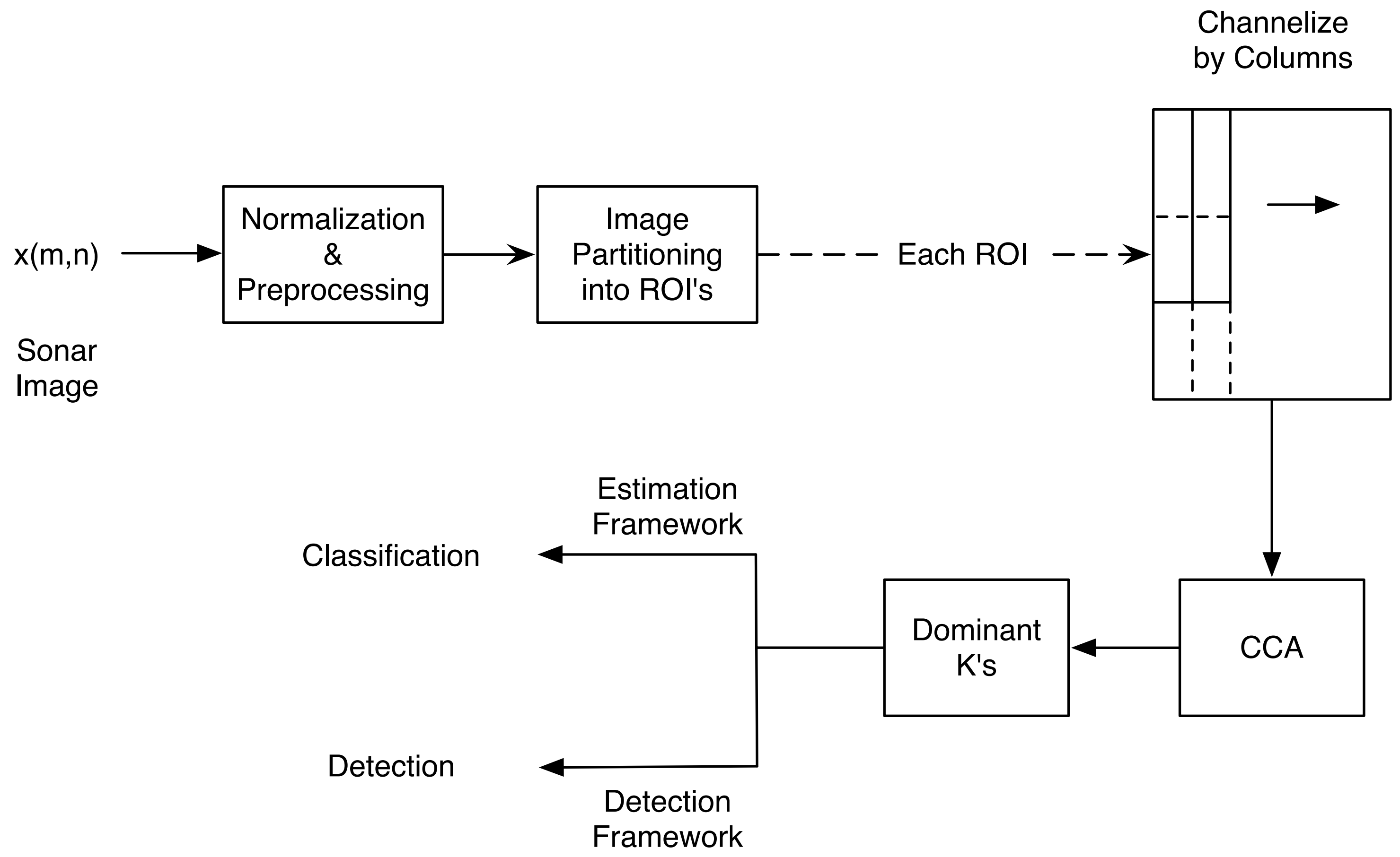


- ✓ A detection measure was then formed for each ROI based on the top 2 canonical coordinates.

$$k_1 \times k_2$$

- ✓ Based on this measure, a threshold was experimentally chosen to make decisions.

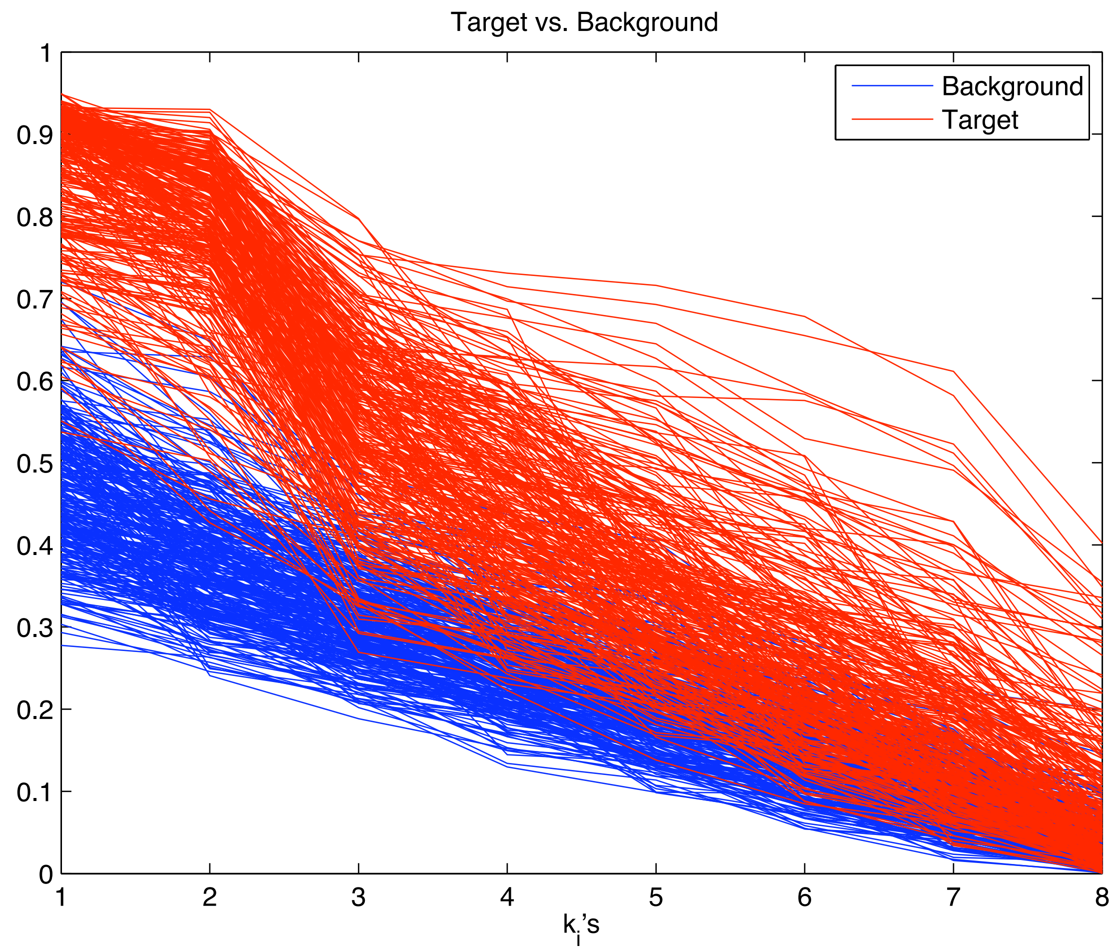
Pre-Processing and Feature Extraction (cont.)



Sonar Image Database

- NSWC Scrub
- Contains 512 Images with 293 images containing 310 targets.
- Set was separated into 3 cases; Easy, Medium, and Hard
  - Easy - low background variation and an overall smooth bottom with targets that are easily identifiable by a skilled operator
  - Medium - contain background clutter and more difficult bottom condition
  - Hard - difficult to detect and classify the targets from a visual inspection due to a high variability of background clutter and very difficult bottom conditions
- To show the separability of the dominant canonical correlations a test was conducted on the entire target set and a random set of same size of random background from all three cases.

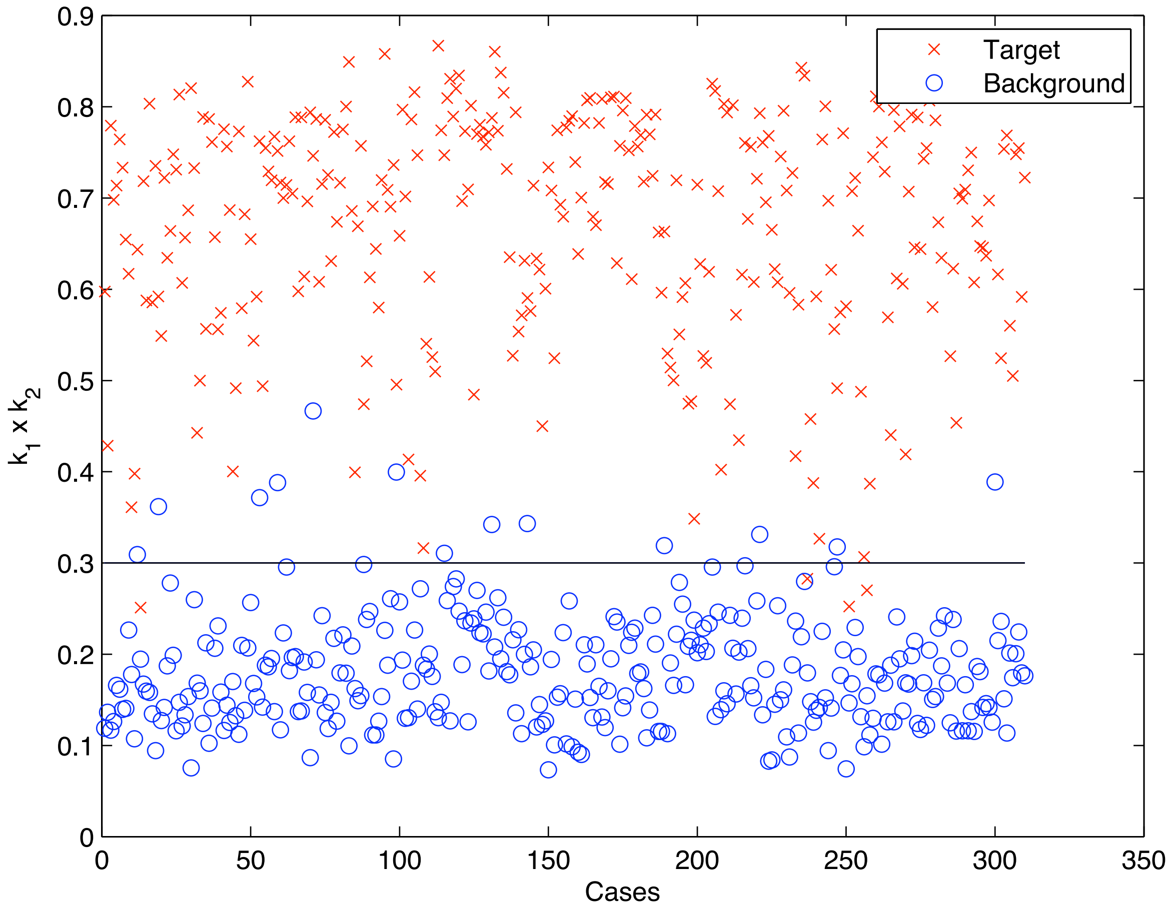
CCA for Detection and Classification of Underwater Objects from Sonar Imagery



✓ Dominant correlations exhibit good separability i.e. more coherence between $\mathbf{x}$ and $\mathbf{y}$ over a target versus background.

CCA for Detection and Classification of Underwater Objects from Sonar Imagery

✓ Using the top 2 canonical correlations the detection scalar measure of $k_1 \times k_2$ was formed and a threshold of 0.3 was determined from sample set.



Detection Results

Easy Cases

- 186 Images containing 201 Targets
- Detected 200 Targets
- Averaged 116 Detections per image

Medium Cases

- 86 Images containing 89 Targets
- Detected 88 Targets
- Averaged 200 Detections per image

Hard Cases

- 21 Images containing 21 Targets
- Detected 20 Targets
- Averaged 213 Detections per image

Detection Results (cont.)

	Detection Rate	False Alarm Rate
Easy	0.99	0.03
Medium	0.99	0.05
Hard	0.95	0.05

- ✓ Targets are detected with high probability and low false alarm rates considering that there are 3800 possible ROI's in an image.
- ✓ Considering the threshold was determined on such a small set of backgrounds the detector performs extremely well on the medium and hard cases averaging around 200 detections per image.
- ✓ The targets that were missed had very little or no shadow structure, i.e. just a bright spot in the image and had the same structure for all three cases.

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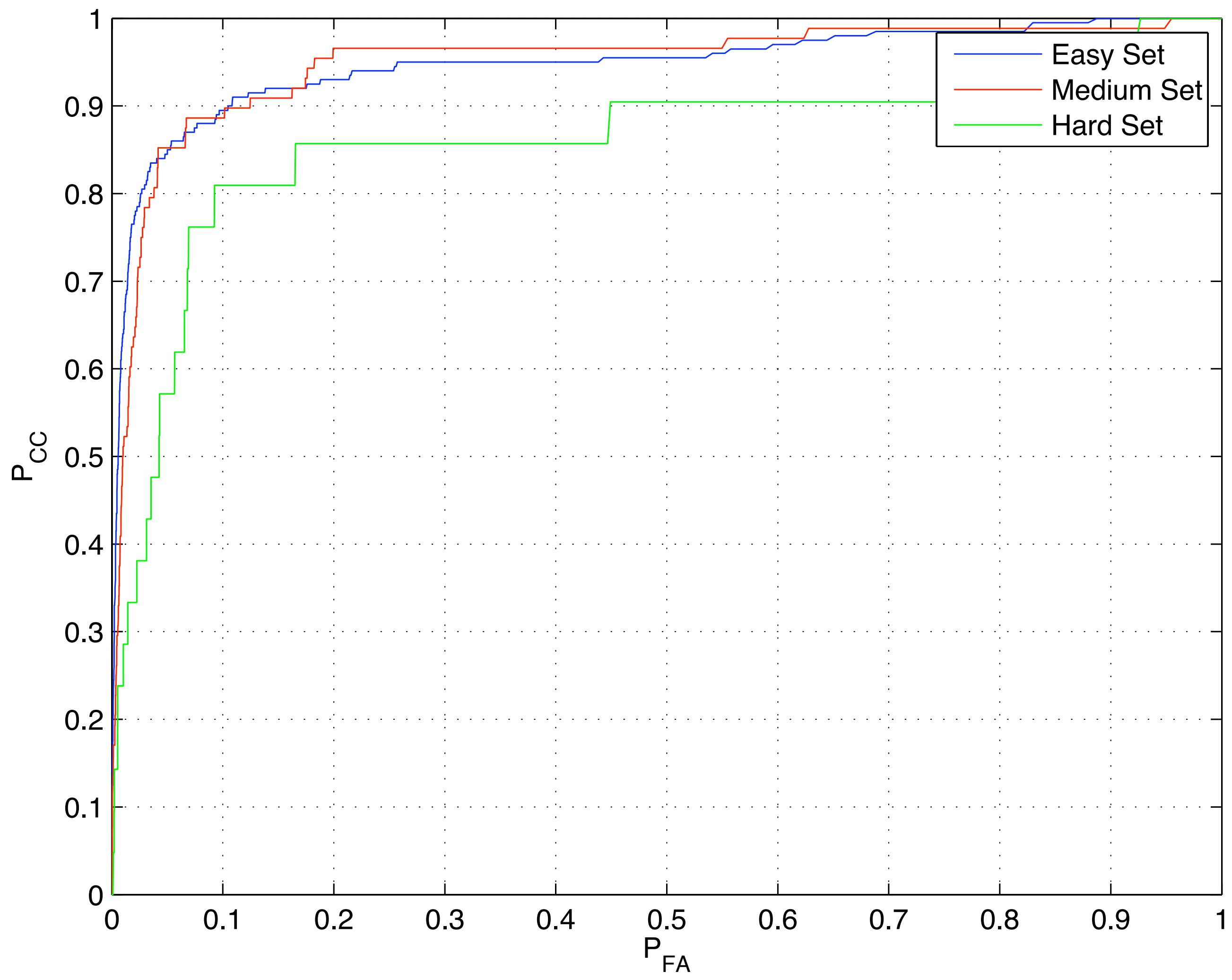
Classification

- ✓ Classification performed with the canonical correlations
- ✓ Training Set
  - 1/2 of target set and same size of non-targets
- ✓ Testing Set
  - 1/2 of target set and rest of non-targets
- ✓ Classifier
  - 2 Layer Back Propagation Neural Network (BPNN)
  - 8 Inputs, 20 neurons in the hidden layer, 2 outputs
- ✓ Overall Results
  - Testing Set
  - 90% P_{cc} / 10% P_{FA}

Classification Results

- ✓ All three cases are detected with high P_{cc} and low P_{FA}
- ✓ Easy Set
  - 90% P_{cc} / 10% P_{FA}
- ✓ Medium Set
  - 90% P_{cc} / 10% P_{FA}
- ✓ Hard Set
  - 84% P_{cc} / 16% P_{FA}



Conclusions and Future Work

- ✓ CCA was used as an optimum Neyman-Pearson detector to detect underwater targets in high-resolution side-looking sonar imagery. The basic idea is that presence of an object (target or non-target) in an ROI changes the coherence level compared to the case when there is no object.
- ✓ Neyman Pearson test in CCA domain only relies on the dominant canonical correlations.
- ✓ Our experimental results on NSWC database demonstrated excellent separability of the dominant canonical correlations of targets and non-targets extracted over ROI's.
- ✓ Using the proposed approach on all of the images detected all targets except 3 out of 310 targets in the data set, while keeping the probability of false alarm rate low.
- ✓ Using the CCA-based classifier, classification was performed with high probability of correct classification and low probability of false alarm

Conclusions and Future Work

✓ Future Work

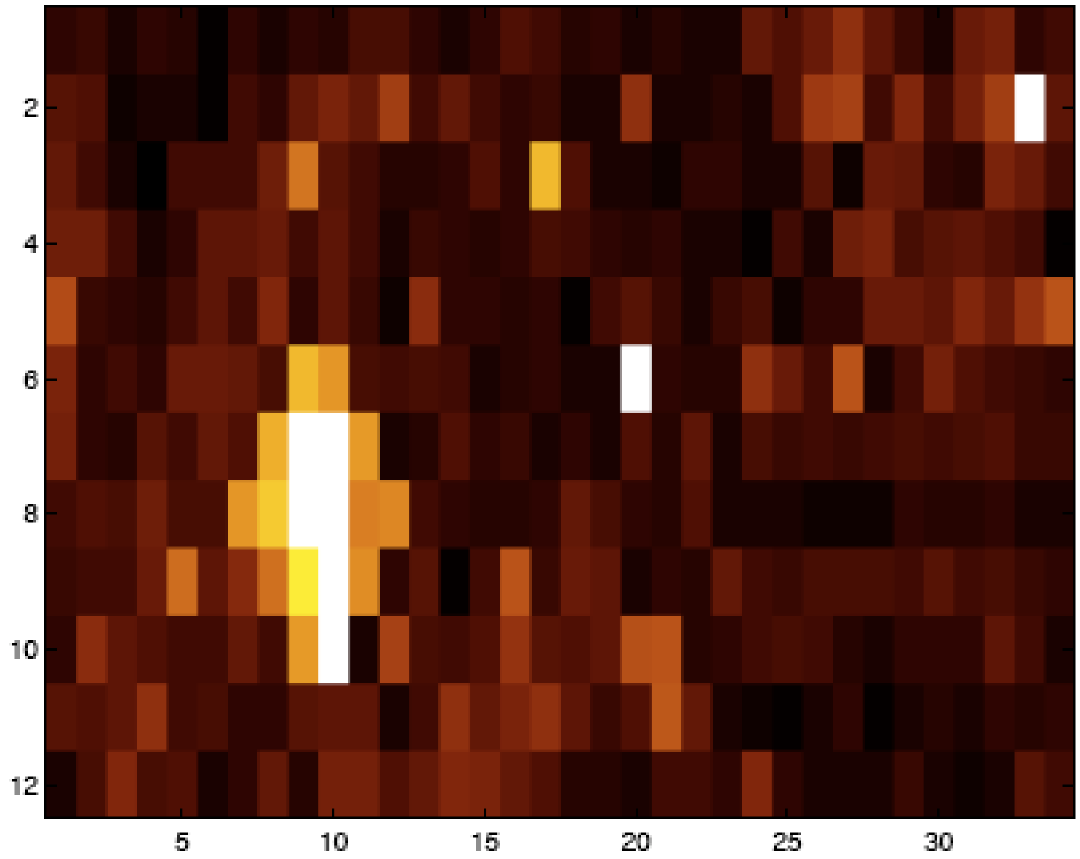
- Explore different 'clever' channelization method to improve the separability of canonical correlations.

- Adaptive threshold selection that depends on background clutter, range-band, etc.

- Moving onto Sonar8 data set for more real application

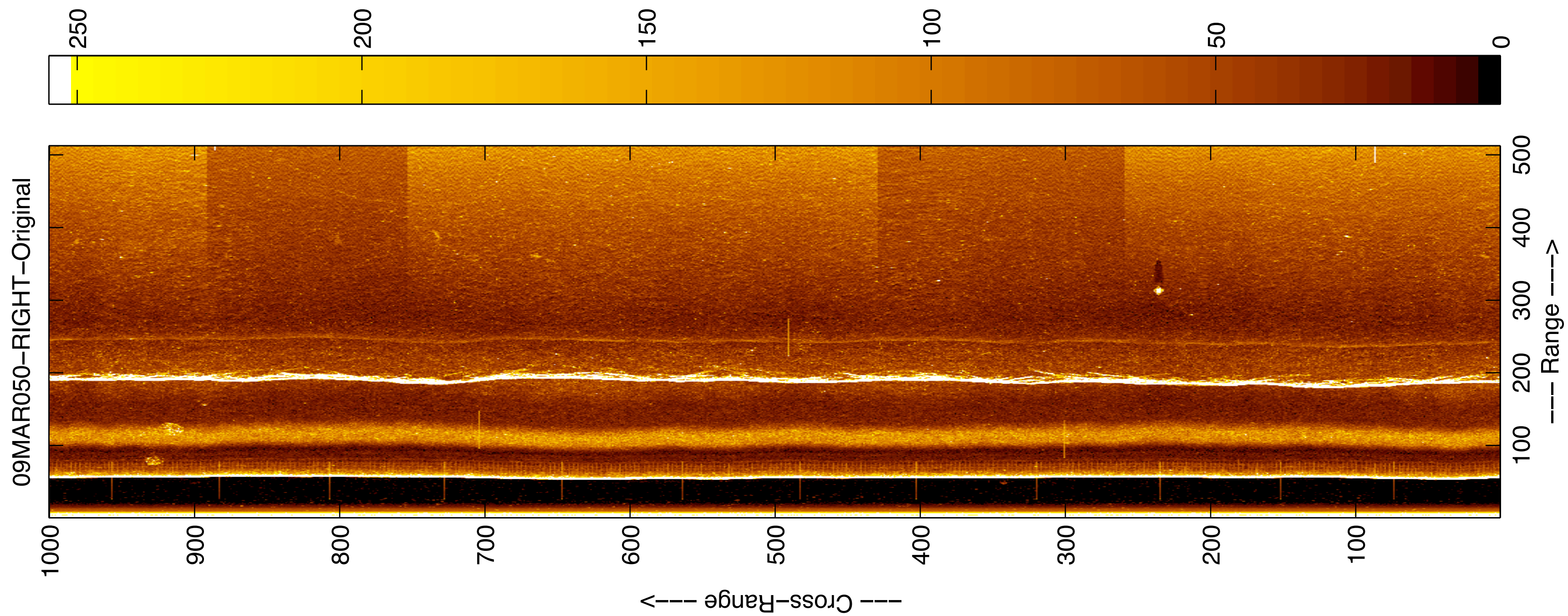
Questions?

Missed Target

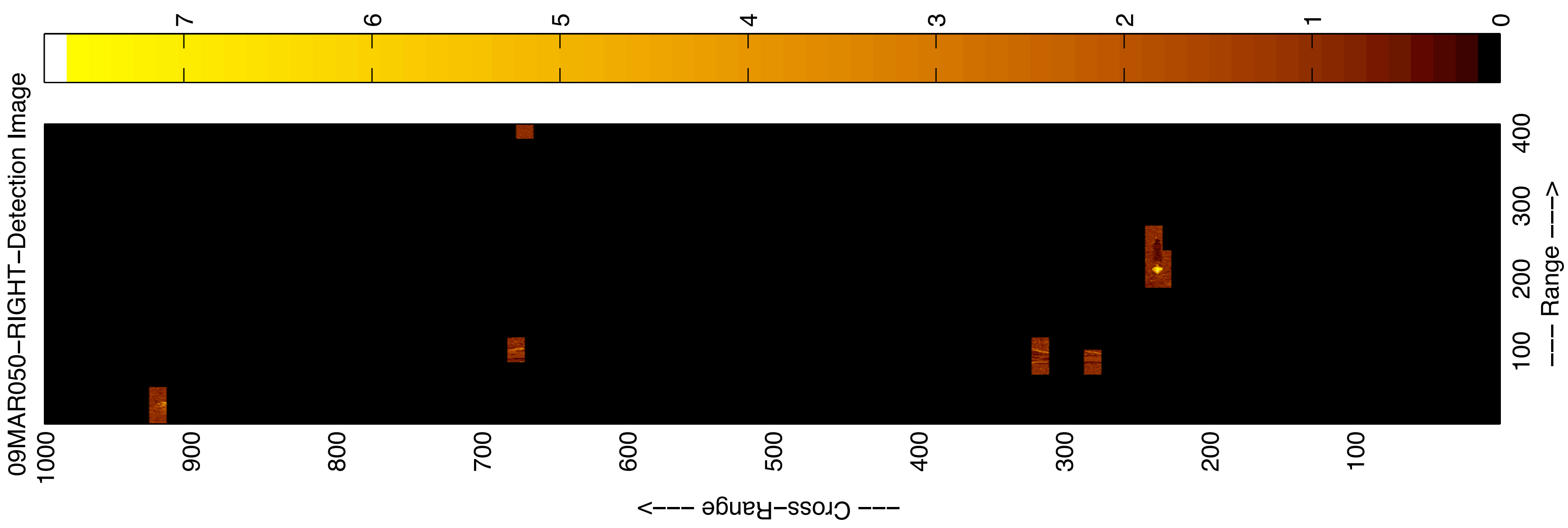


CCA for Detection and Classification of Underwater Objects from Sonar Imagery

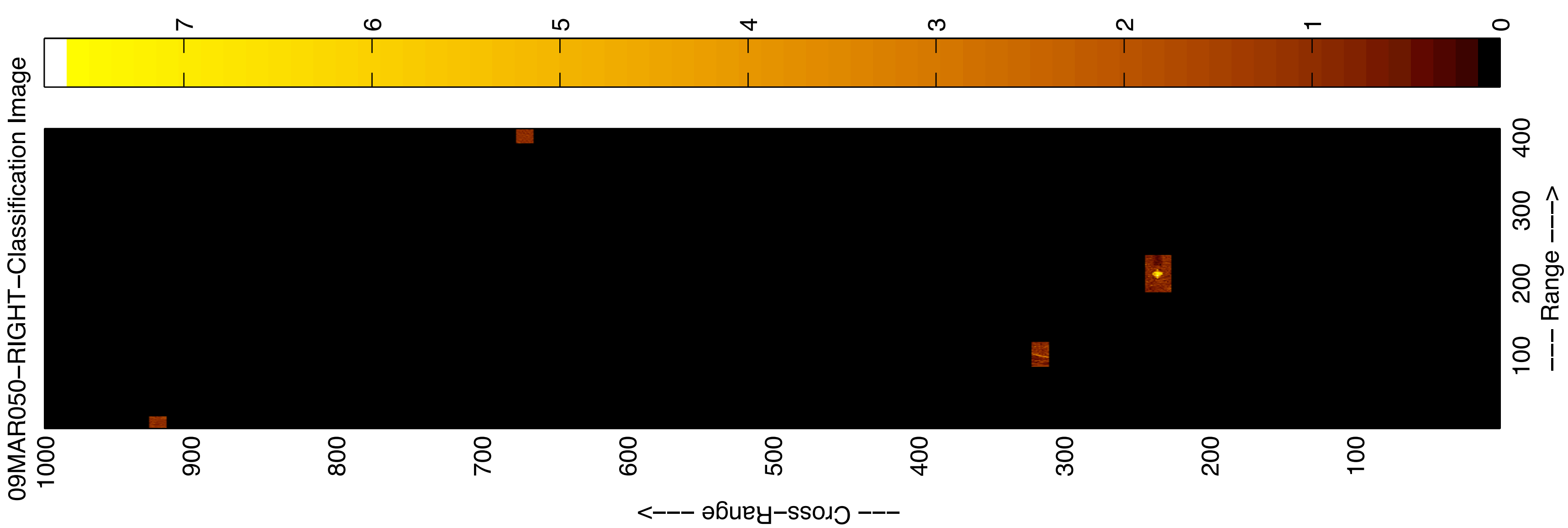
Original Image



Detection Image

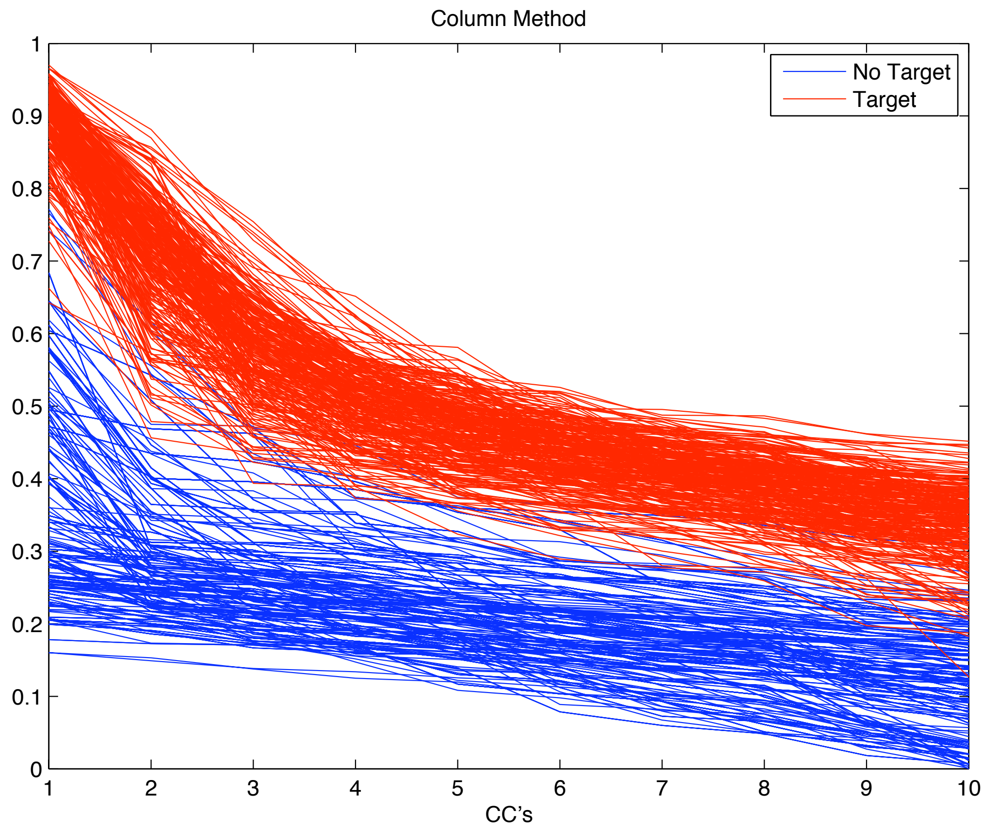


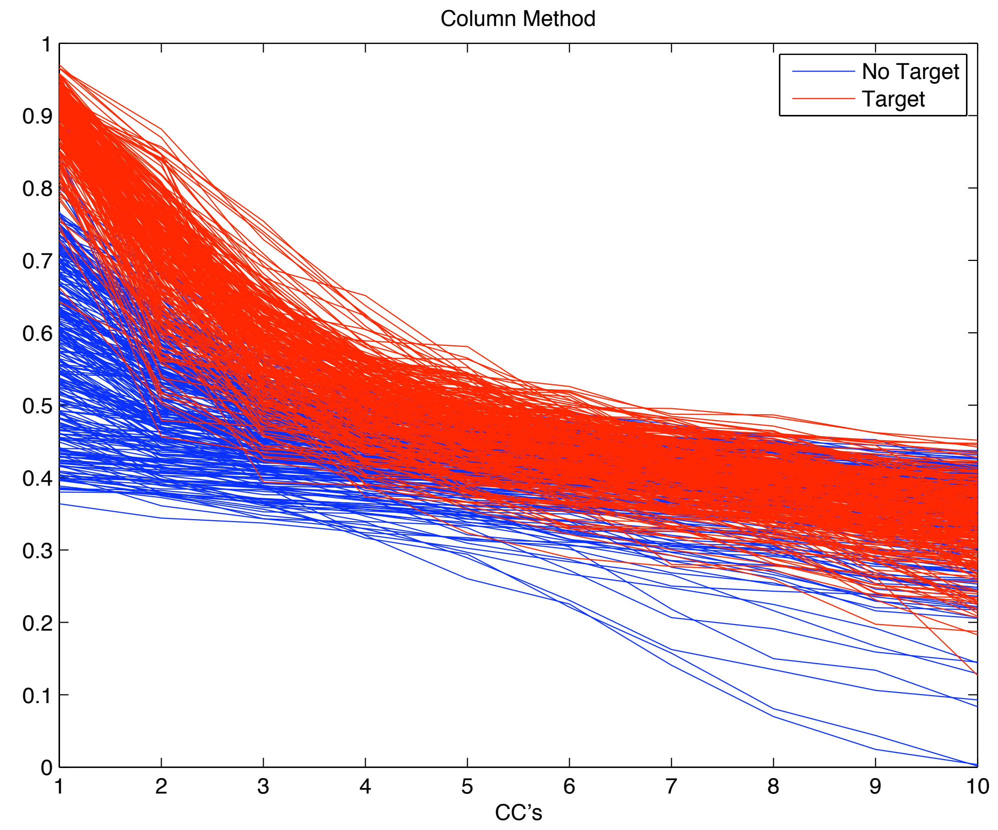
Classification Image



CCA for Detection and Classification of Underwater Objects from Sonar Imagery

Sonar8 Results





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Sonar8 Results