New Acoustic Color and Synthetic Aperture Sonar Processing Methods Using Coherence Analysis

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Neil Wachowski
Department of Electrical and Computer Engineering

Advisor: Dr. Mahmood R. Azimi-Sadjadi
Department of Electrical and Computer Engineering

Committee Members:
Dr. J. Rockey Luo
Department of Electrical and Computer Engineering
Dr. F. Jay Breidt
Department of Statistics

Outline of Presentation

- Introduction
  - Background
  - Research Objectives and Motivations
- Sonar System and Collected Data Sets
- Data Preprocessing and Feature Extraction
  - New Coherence-Based Frequency Subband (CFS) Features
  - Coherence-Based Time Domain (CTD) Features
  - Performance Analysis Using a Single-Aspect Classifier
- Multi-Aspect Classification Systems
  - Classifier Design and Implementation
  - Classification Results on Individual Objects and Entire Runs
- Synthetic Aperture Sonar (SAS) Processing
  - Conventional Delay-and-Sum SAS processing
  - New Coherence-Based Blind SAS Processing
- Conclusions and Future Work

Background

Lit Review

Problem: Develop methods for detection and classification of underwater mine-like objects using broadband acoustic sonar data

- Complicated by many factors including:
  - Man-made and natural clutter
  - Reverberation
  - Changing operating and environmental conditions
  - Lack of *a priori* knowledge about shape and geometry of new non-mine-like objects
- Approaches may be broken down into the following areas:
  - **Sensor development and data acquisition:** Use acoustic source to "ping" the seafloor and capture return signals via hydrophone sensor elements
  - ✓ **Feature extraction:** Extract discriminatory mine-like versus non-mine-like properties from sonar returns
  - ✓ **Detection/classification:** Use extracted features to produce decisions regarding the class of represented objects and environment
  - ✓ **SAS Processing:** Generate synthetic image of seafloor by coherently integrating acoustic sonar data from multiple sensors and pings

Research Objectives and Motivations

Research Objectives:

1) Development of a feature extraction method that exploits coherence across two sonar pings in specific frequency subbands
   - Offer a theoretically and intuitively meaningful way of performing acoustic color processing
2) Development of new multi-aspect classifiers
3) Development of a coherence-based blind SAS processing algorithm
   - Does not require use of vehicle motion parameters
4) Demonstrate the effectiveness of these tools on two real sonar databases

Motivations:

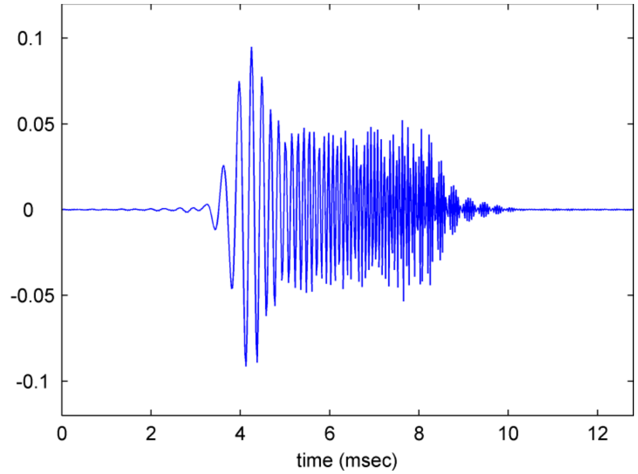
- Using multiple sonar pings/aspects can improve classification performance since a single ping may not contain enough discriminatory information
- Ping-to-ping coherence patterns in subbands of an object's frequency response are a better indicator of its type than coherence in different blocks of range cells (i.e. sonar time series)
- Conventional SAS processing requires elaborate platform motion estimation and compensation, and produces images that do not covey information useful for object classification

Sonar System

- Data collected by wing Buried Object Scanning Sonar (BOSS)
  - Developed by Florida Atlantic University
- Produces omnidirectional 5 millisecond linear FM transmit signal over 3-19 kHz
- Sonar returns captured by 40 hydrophone elements
  - Uniform linear subbarray of 20 hydrophones on each wing of "Bluefin 12" unmanned underwater vehicle (UUV)

Bluefin 12 UUV with wing BOSS payload

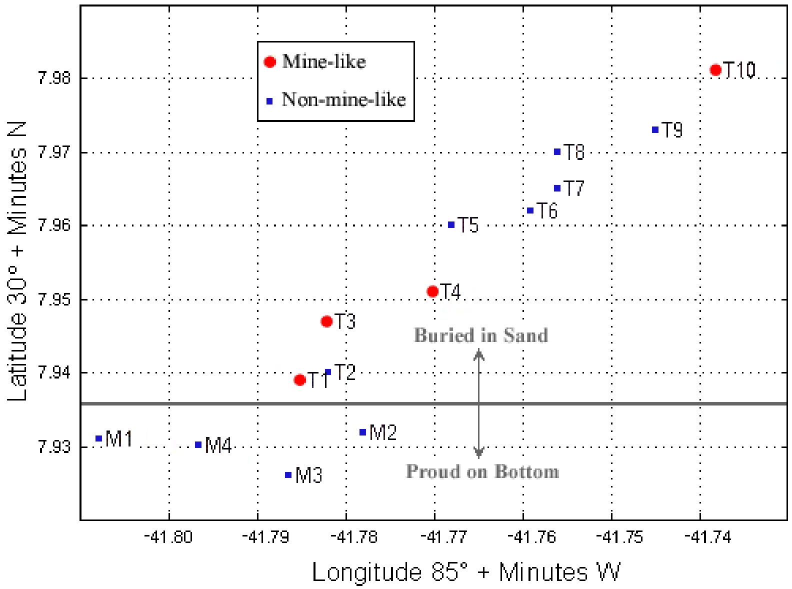
Transmit Signal



Collected Data Sets

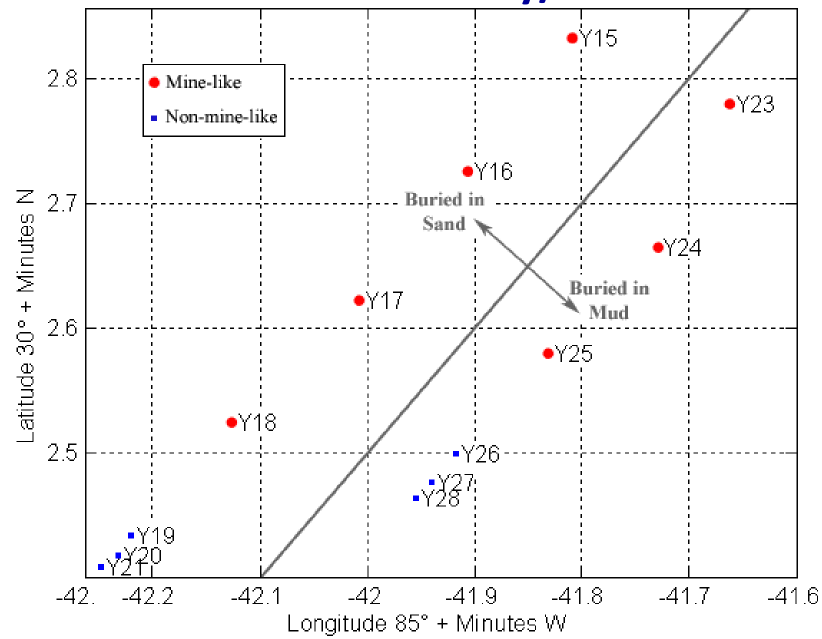
Davis Objects
UUV Paths

Davis Point Data Set – March 2007



- Ping rate: 25 pings/sec UUV speed: 1.5 m/s UUV altitude: 3 m
- UUV made 'star-shaped' runs centered on objects T1, T3, T4, T5, and T10, and diagonal runs that traversed entire target field
- Each object adequately captured during at least one run
- Objects with properties similar to mines used

Yankee Data Set – May/June 2006



- Ping rate: 20 pings/sec UUV speed: 1.5 m/s UUV altitude: 3 m or 12 m
- UUV made multiple runs over each object
- All objects adequately captured besides Y23 and Y24
- Real mines used, but object characteristics not provided
- Two bottom types: **sand** and **mud**

CFS Signal Preprocessing

Subband Decomp.

- Sonar return at ping *p*: $x_p[n] = h_p[n] * s[n] + f_p[n] * s[n] + v_p[n]$
  - $s[n]$ = transmit signal, $h_p[n]$ = impulse response of object and bottom

    $f_p[n]$ = impulse response of correlated noise, $v_p[n]$ = uncorrelated noise
- Extract transfer function of object and bottom:
  - Apply matched filter to better separate object and bottom return from other returns and correlated noise. In the frequency domain:

$$X_p[k]S^*[k] = H_p[k]\,|S[k]|^2 + F_p[k]\,|S[k]|^2 + V_p[k]S^*[k]$$

  - Remove effects of transmit signal using inverse filter:

$$\frac{X_p[k]S^*[k]}{|S[k]|^2 + \epsilon} \approx H_p[k] + F_p[k] + \frac{V_p[k]}{S[k]}$$

  - Window to remove correlated noise:

$$\hat{H}_p[k] \approx H_p[k] + W[k] * \frac{V_p[k]}{S[k]}$$

- Forms “clean” frequency response of bottom and object within bandwidth of transmit signal (3-19 kHz for BOSS)

Canonical Correlation Analysis (CCA) Review

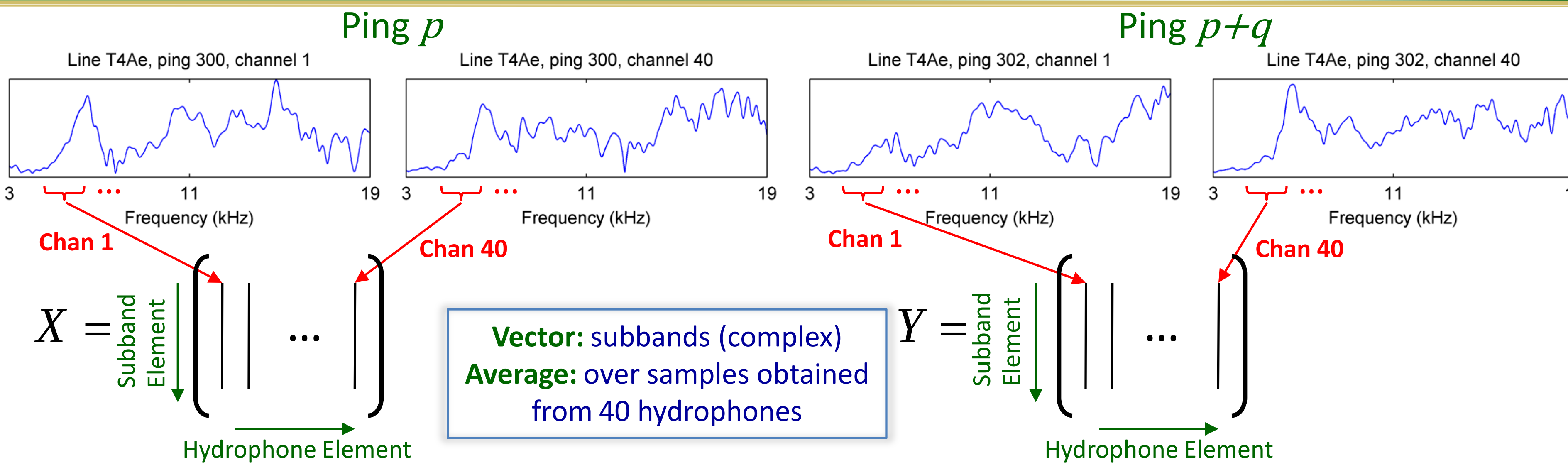
- Given zero-mean vectors: $\mathbf{x} \in \mathbb{R}^m$ and $\mathbf{y} \in \mathbb{R}^n$ with $m \leq n$
- Composite covariance matrix: $\boxed{E\left[\begin{pmatrix}\mathbf{x}\\ \mathbf{y}\end{pmatrix}\begin{pmatrix}\mathbf{x}^T & \mathbf{y}^T\end{pmatrix}\right] = \begin{bmatrix}\mathrm{R}_{xx} & \mathrm{R}_{xy}\\ \mathrm{R}_{yx} & \mathrm{R}_{yy}\end{bmatrix}}$
- **Coherence matrix**: $\boxed{\mathrm{C} = E[\boldsymbol{\zeta}\boldsymbol{\nu}^T] = E[(\mathrm{R}_{xx}^{-1/2}\mathbf{x})(\mathrm{R}_{yy}^{-1/2}\mathbf{y})^T] = \mathrm{R}_{xx}^{-1/2}\mathrm{R}_{xy}\mathrm{R}_{yy}^{-T/2}}$
- SVD of Coherence Matrix: $\boxed{\mathrm{C} = \mathrm{FKG}^T}$ $\mathrm{F} \in \mathbb{R}^{m\times m}$ and $\mathrm{G} \in \mathbb{R}^{n\times n}$ orthogonal
- $\mathrm{K} = \mathrm{diag}[k_1, k_2, \ldots, k_m]$ is the matrix of **canonical correlations** with $1 \geq k_1 \geq k_2 \geq \ldots \geq k_m > 0.$
- **Canonical coordinates** $\mathbf{u}$ and $\mathbf{v}$:

$$\boxed{\begin{bmatrix}\mathbf{u}\\ \mathbf{v}\end{bmatrix} = \begin{bmatrix}\mathrm{F}^T & \mathbf{0}\\ \mathbf{0} & \mathrm{G}^T\end{bmatrix}\begin{bmatrix}\boldsymbol{\zeta}\\ \boldsymbol{\nu}\end{bmatrix} = \begin{bmatrix}\mathrm{F}^T & \mathbf{0}\\ \mathbf{0} & \mathrm{G}^T\end{bmatrix}\begin{bmatrix}\mathrm{R}_{xx}^{-1/2} & \mathbf{0}\\ \mathbf{0} & \mathrm{R}_{yy}^{-1/2}\end{bmatrix}\begin{bmatrix}\mathbf{x}\\ \mathbf{y}\end{bmatrix}}$$

- It follows that: $\boxed{\mathrm{K} = E[\mathbf{u}\mathbf{v}^T] = \mathrm{F}^T\mathrm{C}\mathrm{G}}$

CFS Feature Extraction

CCA Review



- CCA used to measure coherence between same subband at pings p and $p+q$ (q is ping separation), thus producing *L* canonical correlations (*L* = subband size)
- Dominant canonical correlation ($k_p^{(m)}(1)$) used as feature to represent subband m
- Find features ($k_p^{(m)}(1)$ values) that most effectively discriminate between mine-like and non-mine-like objects using Fisher discrimination measure:

$$J_m = \frac{\left|\mu_1^{(m)} - \mu_2^{(m)}\right|}{\sigma_1^{(m)} + \sigma_2^{(m)}}, \qquad m \in [0, M-1]$$

$\mu_i^{(m)}$: mean of k_1 values from *m*th subband of class *i* pings

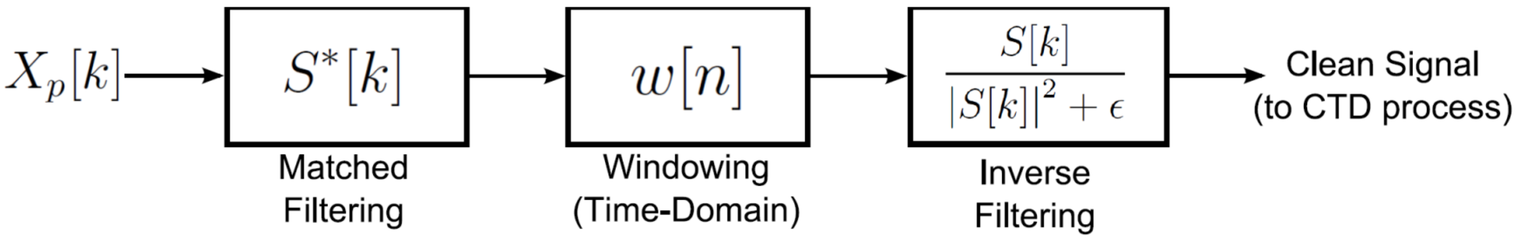
$\sigma_i^{(m)}$: std. deviation of k_1 values from *m*th subband of class *i* pings

- 20 features with largest J_m used to form feature vector representing ping p

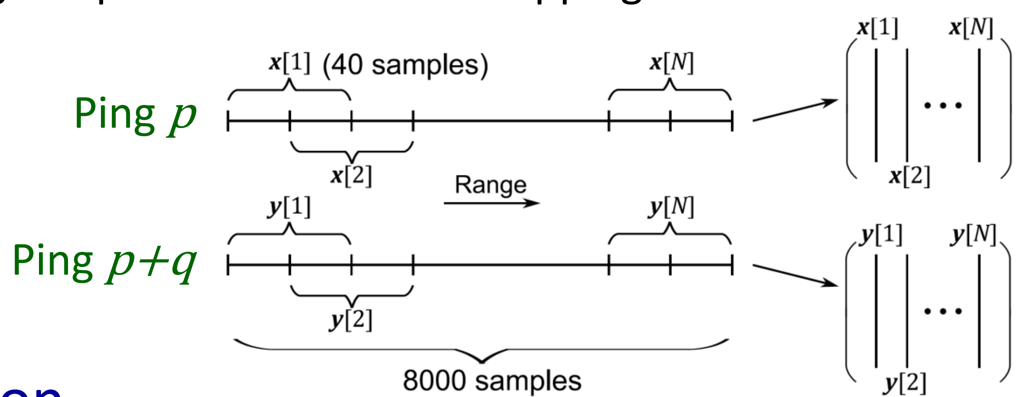
CTD Feature Extraction

CCA Review

- ## Preprocessing
  - Matched filtering, windowing, and inverse filtering still employed:



- ## Data Setup
  - Recovered times series (200 samples) from each receiver (40 total) are concatenated
  - Concatenated signals partitioned into overlapping blocks of size 40 samples with 50% overlap



- ## Feature Extraction
  - CCA performed between the two data channels (sonar returns with some separation)
  - Produces 40 canonical correlations with 20 dominant canonical correlations used to form feature vector to represent ping p

Feature Space Properties of Data Sets

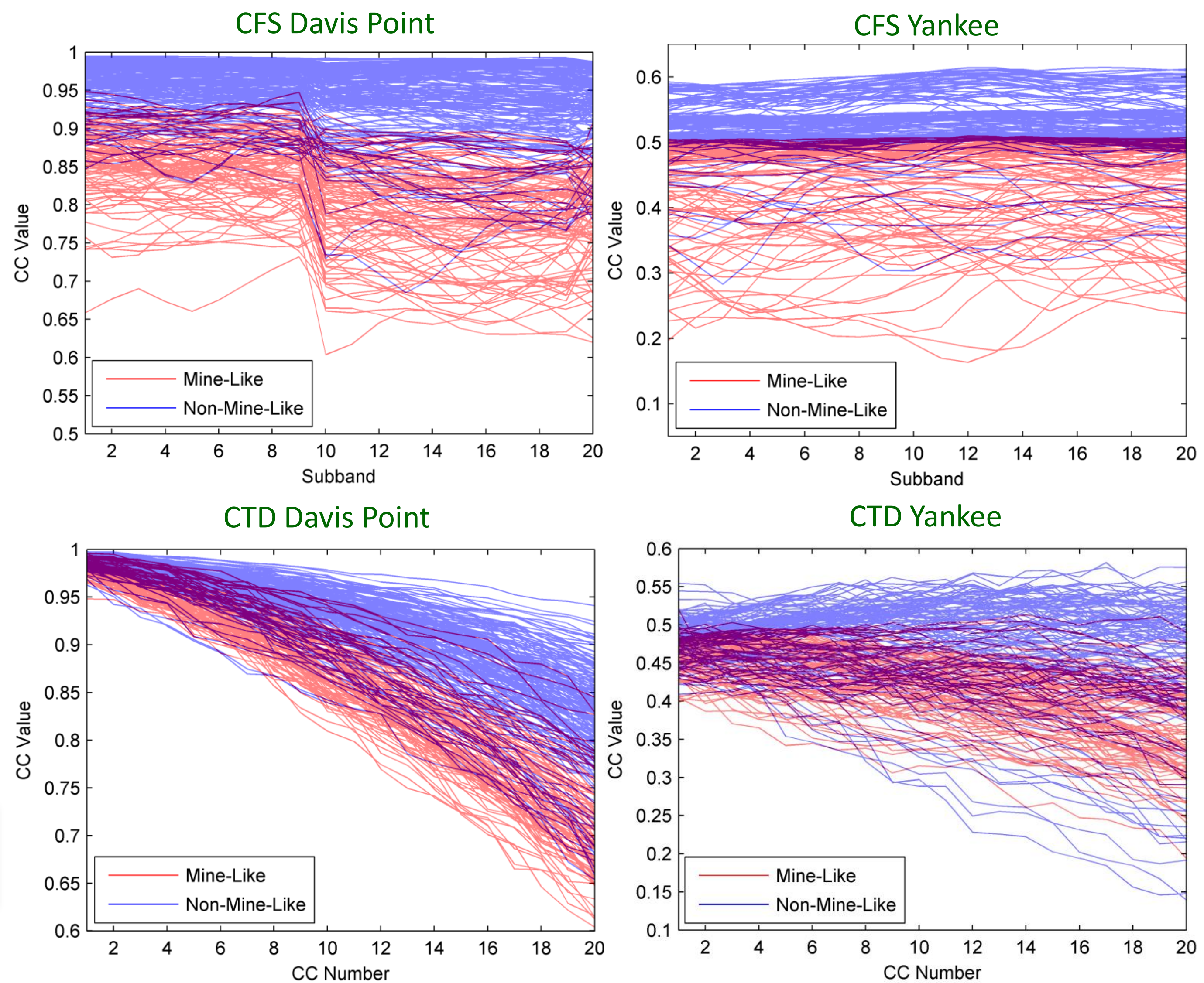
Normalization

Colorado State University

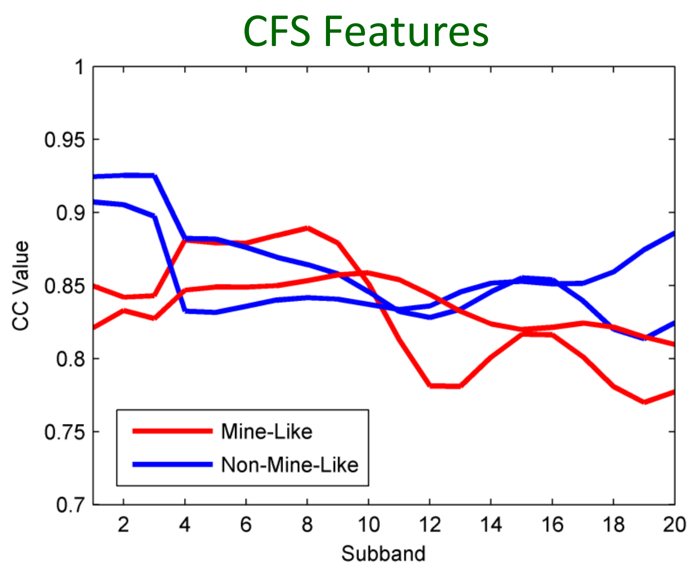
- Both CFS and CTD feature spaces show some separation
- Fewer instances where CFS non-mine-like features show similar levels of coherence to CFS mine-like features (compared to CTD)
- To make Yankee feature vectors from different runs compatible, they were normalized

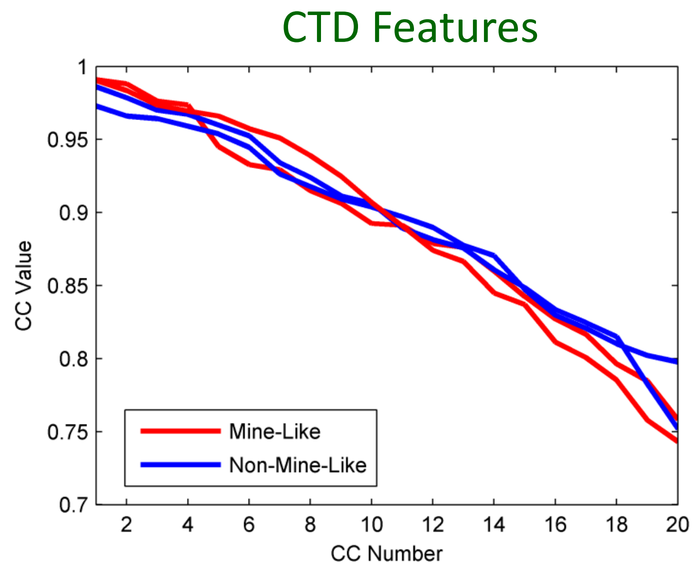
Ping Separation: q = 2 for both feature types and data sets

Feature Vector Plots:

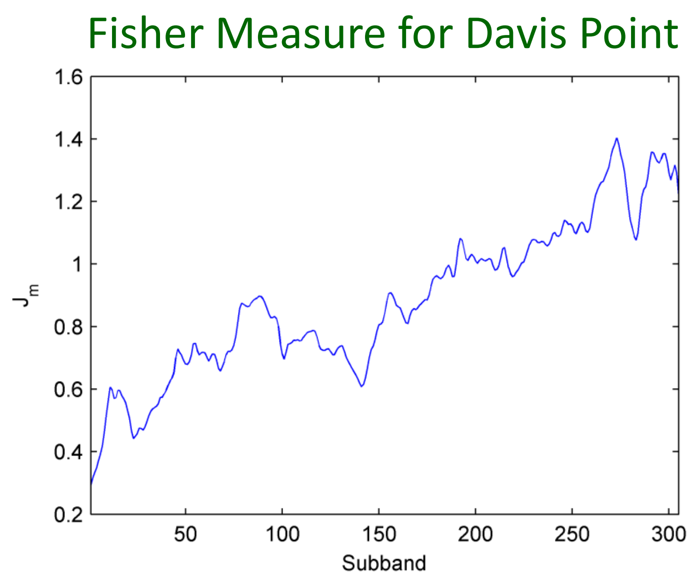


Feature Space Properties of Data Sets





- CFS coherence patterns more useful for classification
  - CFS feature vectors that overlap are more discernable
  - CTD feature vectors are monotonically non-increasing regardless of object type
- High frequency subbands are more useful for classification of objects in Davis Point data set
  - Features extracted using samples in ranges 17.16-17.27 kHz and 18.11-18.95 kHz used to form each feature vector



Single-Aspect Classification Results

Absolute Rates
UUV Paths

- Back-propagation neural network (BPNN) used to classify individual feature vectors
  - Highlights performance differences between CFS and CTD feature extraction methods

Davis Point Data: Percent Incorrect Classification

	Validation	Testing 1	Testing 2
CFS Features	8.0%	7.9%	10.7%
CTD Features	12.0%	13.9%	21.4%
Reduction	**33.3%**	**43.2%**	**50.0%**

- Pings in training and validation set come from runs in 'star-shaped' groups
  - Contains sonar returns from objects T1, T3, T4, T5, T6, T9, T10, and M2
- Pings in first testing set come from different runs in 'star-shaped' groups
  - Contains sonar returns from objects T1, T2, T3, T4, T5, T6, T10, and M3
- Pings in second testing set come from long Southwest-Northeast runs
  - Contains sonar returns from objects T1, T3, T5, T6, T7, T8, T9, T10, M1, and M4
- Objects captured from different aspects

Yankee Data: Percent Incorrect Classification

	Validation	Testing 1	Testing 2
CFS Features	6.8%	6.8%	12.7%
CTD Features	0%	18.6%	25.5%
Reduction	-	**63.4%**	**50.2%**

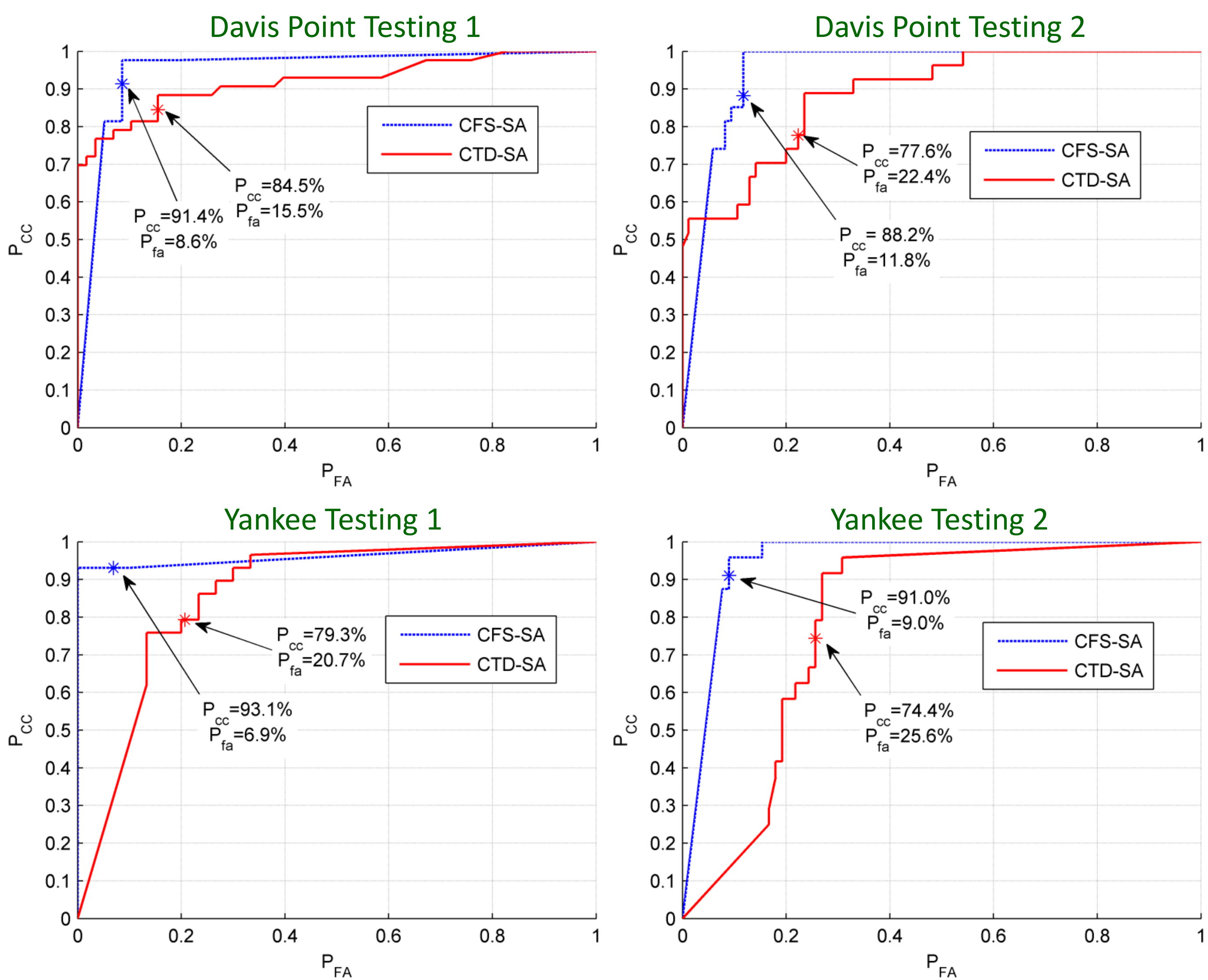
- Pings in training and validation set come from objects buried in sand (Y15, Y16 (12 m altitude), Y17, Y19, Y20, and Y21)
- Pings in first testing set come from different runs over objects buried in sand (Y15, Y17, Y18, Y19, Y20, and Y21)
- Pings in second testing set come from objects buried in mud (Y25, Y26, Y27, and Y28)
- Pings used in different data sets capture different aspects of each object when possible
- CFS features perform worse on validation set due to misclassification of single ping off center of each mine-like object

Single-Aspect Classification Results

Receiver Operating Characteristic (ROC) Curves:

Using CFS features provides:

- Higher correct classification rates in almost every case
- Better performance as measured by ROC curves
- Superior generalization ability



CFS-SA = CFS single-aspect classifier
CTD-SA = CTD single-aspect classifier

CMAC Details

Collaborative Multi-Aspect Classifier (CMAC)

- N agents, where each makes a preliminary decision, u_i , on a separate feature vector $\mathbf{x}_i$ using a probabilistic neural network (PNN)
- Each agent shares its decision with all other agents via a coordinator.
- BPNN in each agent estimates class conditional probabilities of other agent's decisions (elements of $\mathbf{u}_{ir}$)
- ith agent makes final decision u_{fi} in data fusion center using:

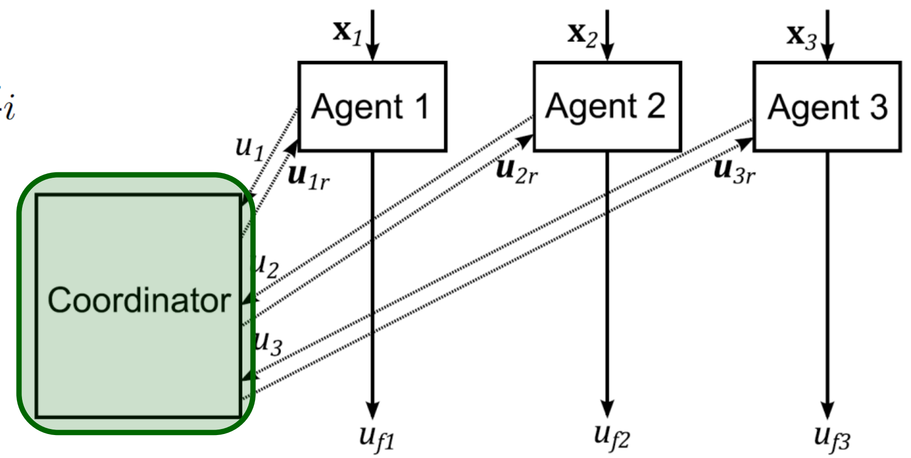
PNN Outputs

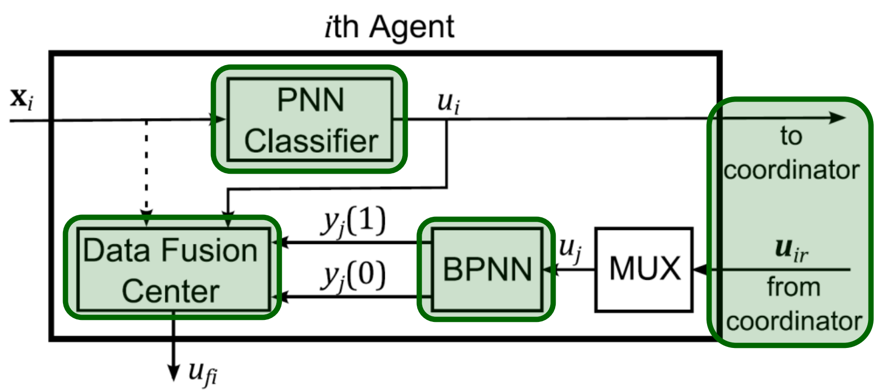
Prior Probabilities

BPNN Outputs

Decision Costs

$$\frac{p(C_1|\mathbf{x}_i)}{p(C_0|\mathbf{x}_i)} \underset{u_{fi}=0}{\overset{u_{fi}=1}{\gtrless}} \frac{P(C_1)^{N-1}\prod_{j=1,j\neq i}^{N} p(C_0|u_j)\,[J_{10}-J_{00}]}{P(C_0)^{N-1}\prod_{j=1,j\neq i}^{N} p(C_1|u_j)\,[J_{01}-J_{11}]}$$



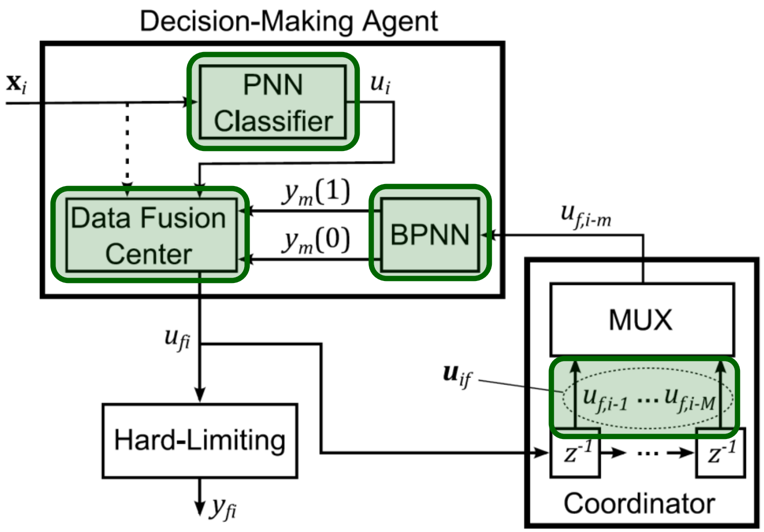


- Minimizes the expected cost of making an incorrect decision

Classifier Designs

DF Details

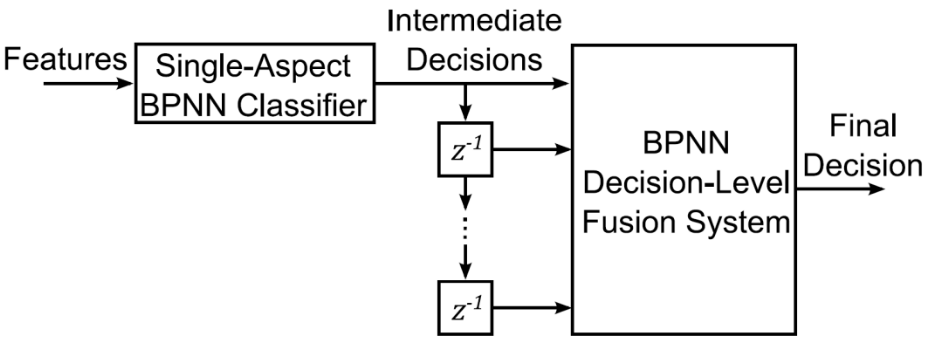
Decision Feedback (DF) Based on One-Agent CMAC



- Generates final decision u_{fi} using:
  - Preliminary decision on current ping
  - Class conditional probabilities of final decisions at M previous pings
  - Likelihood ratio:

$$u_{fi} = \frac{P(C_0)^M p(C_1|\mathbf{x}_i) \prod_{m=1}^{M} p(C_1|u_{f,i-m})}{P(C_1)^M p(C_0|\mathbf{x}_i) \prod_{m=1}^{M} p(C_0|u_{f,i-m})}$$

Nonlinear Decision-Level Fusion (NDLF)



- N intermediate decisions on N separate features produced using single-aspect BPNN
- Final decision formed by fusing intermediate decisions using second BPNN
  - Trained using sets of N single-aspect decisions
  - Incapable of using variable number of pings

Multi-Aspect Classification Results

Absolute Rates
MA ROC Results

Davis Point Data: Percent Incorrect Classification

	Validation	Testing 1	Testing 2
CMAC	4.0%	2.0%	6.2%
DF	8.0%	4.0%	8.0%
NDLF	6.0%	8.9%	8.0%
Reduction (CMAC vs. NDLF)	**33.3%**	**77.5%**	**22.5%**

Yankee Data: Percent Incorrect Classification

	Validation	Testing 1	Testing 2
CMAC	0%	3.4%	5.9%
DF	2.3%	5.1%	8.8%
NDLF	0%	5.1%	8.8%
Reduction (CMAC vs. NDLF)	**0%**	**33.3%**	**33.0%**

- CFS feature vectors used
- Same training, validation, and testing sets used for single-aspect classifier results are used for multi-aspect classifier results
- CMAC: 3 agents, DF: 2 previous decisions, NDLF: 3 intermediate decisions
- CMAC provides highest correct classification rate in every case
  - Corrects nearly every instance of misclassification of center pings off mine-like objects produced by single-aspect classifier
  - Only one object (Y27 in Yankee data set) had majority of pings misclassified

Simultaneous Detection and Classification

- Two Davis Point runs (top) and two Yankee runs (bottom)
- Largest improvement when using CFS over CTD feature vectors
- CMAC provides most accurate classification

Additional Runs

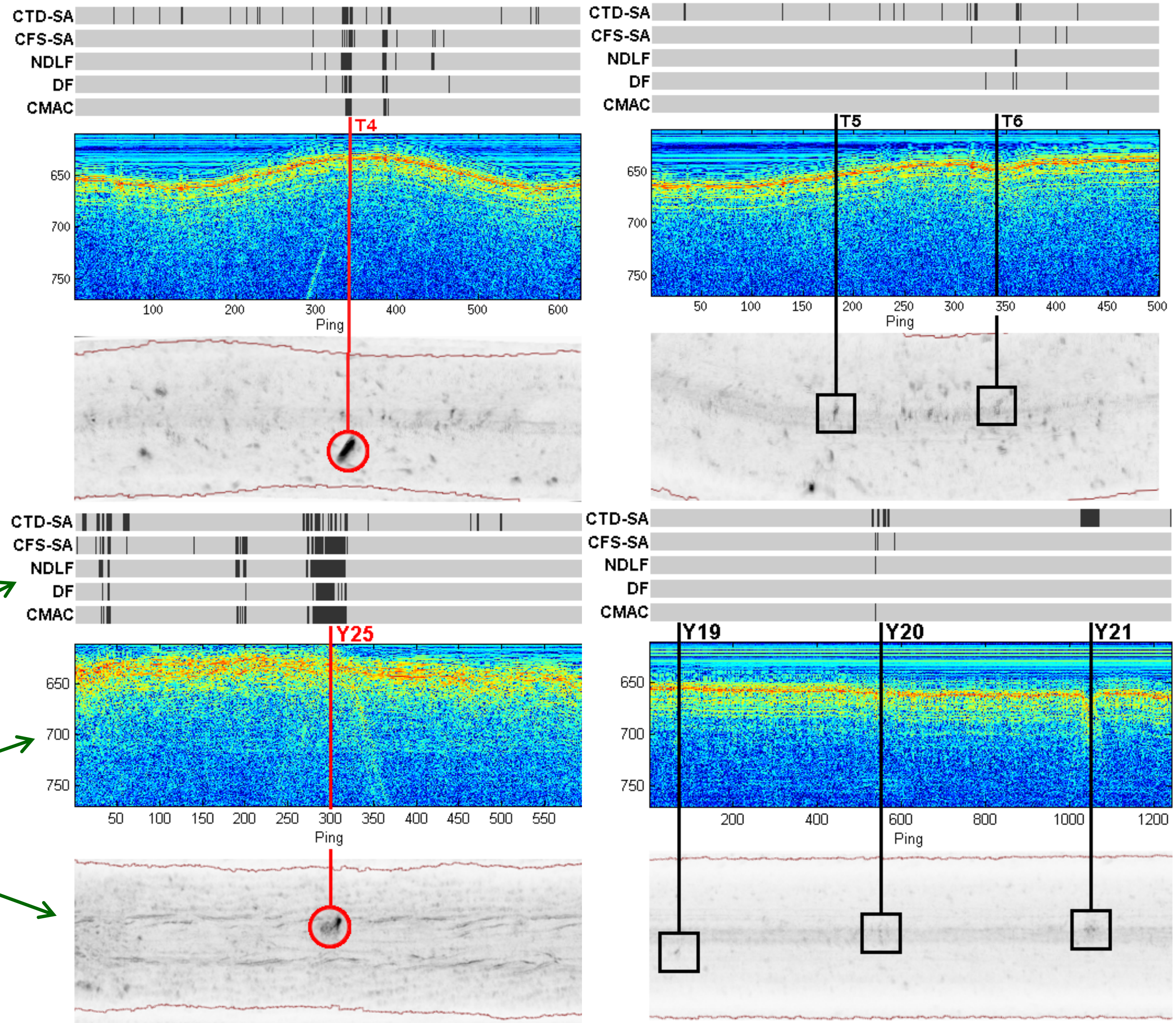
Detection/classification strips where potential mine-like objects are shown by black vertical bars

Matched filtered image

SAS image showing relative target locations

Targets in red

Non-targets in black



Delay-and-Sum SAS Processing

- Several 3-D SAS frames generated by coherently integrating data from *M* pings and *N* hydrophones
  - Frame pixels correspond to specific focal points of seafloor
  - Time sample selected from sonar return collected by each hydrophone at each ping that corresponds to focal point
  - SAS frame $\mathrm{A}(x, y, z, k)$ generated using:

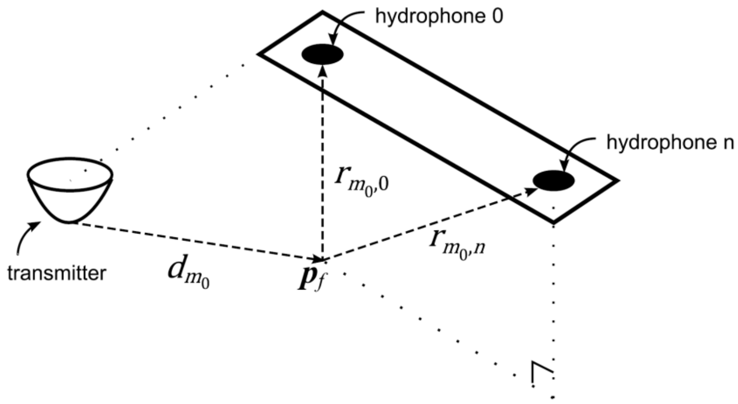
$$\boxed{\mathrm{A}(x,y,z,k) = \sum_{n=1}^{N} \sum_{m=k}^{k+M-1} s_{m,n}[t_{m,n}^{(\mathbf{p}_f)}] d_m r_{m,n}}$$

$s_{m,n}[t]$ = sonar return for ping *m* and hydrophone *n*

$t_{m,n}^{(\mathbf{p}_f)}$ = time sample for focal point $\mathbf{p}_f = [p_x, p_y, p_z]$ $\Rightarrow$ $x = \dfrac{p_x}{\Delta p_x}, y = \dfrac{p_y}{\Delta p_y}, z = \dfrac{p_z}{\Delta p_z}$

Focal Point Spacing

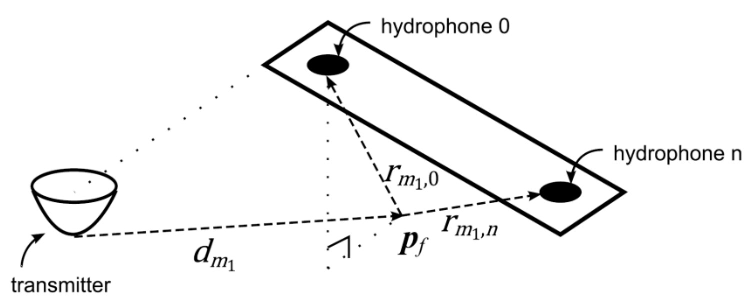
Ping m_0



- SAS frames combined by overlapping and using max intensity pixel at each focal point:

$$\boxed{\mathrm{B}(x,y,z) = \max_k[\mathrm{A}(x,y,z,k)]}$$

Ping m_1



- 2-D SAS image generated using max intensity range value for each point along and across track:

$$\boxed{\mathrm{P}_z(x,y) = \max_z[\mathrm{B}(x,y,z)]}$$

Coherence-Based Blind SAS Processing

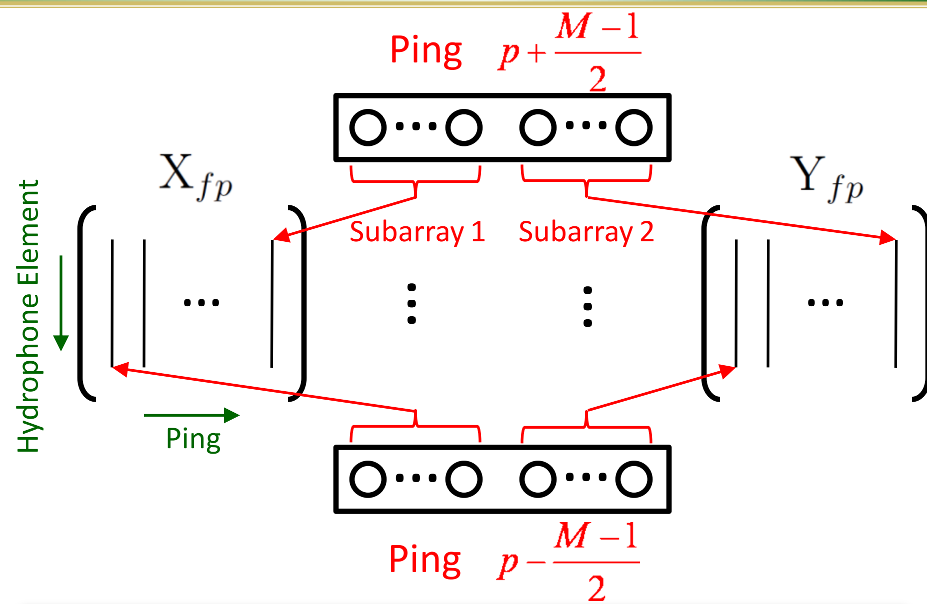
CCA Review

- Generates image that displays information in ping-frequency (fp) plane
  - Images useful for determining objects' along track location **and class label**

For each frequency sample from 3-19kHz (10.5 Hz per bin):

- Perform CCA between data from two subarrays (one for each wing of BOSS)
  - Vector: hydrophone subarray (N/2 elements)
  - Average: over *M* pings
- Find canonical coordinate samples:

$$\mathrm{U}_{fp} = \mathrm{F}_{fp}^{H}(\mathrm{R}_{XX}^{(fp)})^{-1/2}\mathrm{X}_{fp} = \begin{bmatrix} \mathbf{u}_{fp}^{(1)} \\ \vdots \\ \mathbf{u}_{fp}^{(N/2)} \end{bmatrix}$$



No platform motion estimation required!

- Each pixel formed using average of *L* $\mathbf{u}_{fp}^{(1)}$ samples in center of ping window:

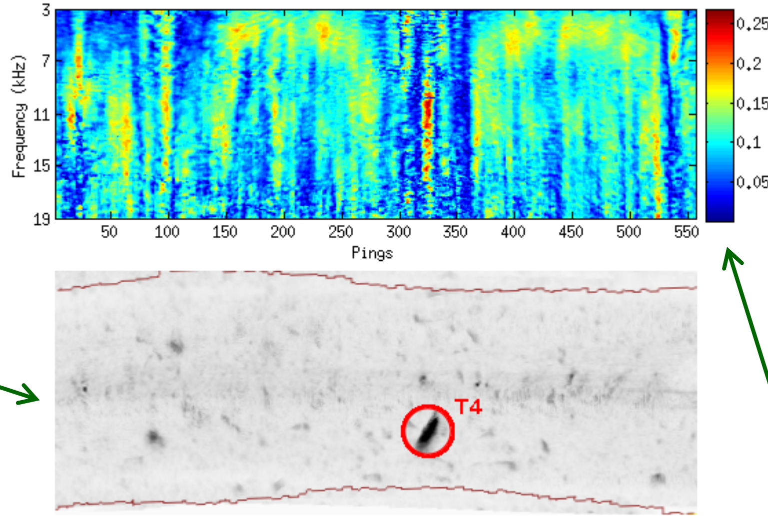
$$S(f,p) = \left|\frac{1}{L}\sum_{j}\mathbf{u}_{fp}^{(1)}(j)\right|, j \in \left[\frac{1}{2}(M-L+2), \frac{1}{2}(M+L)\right]$$

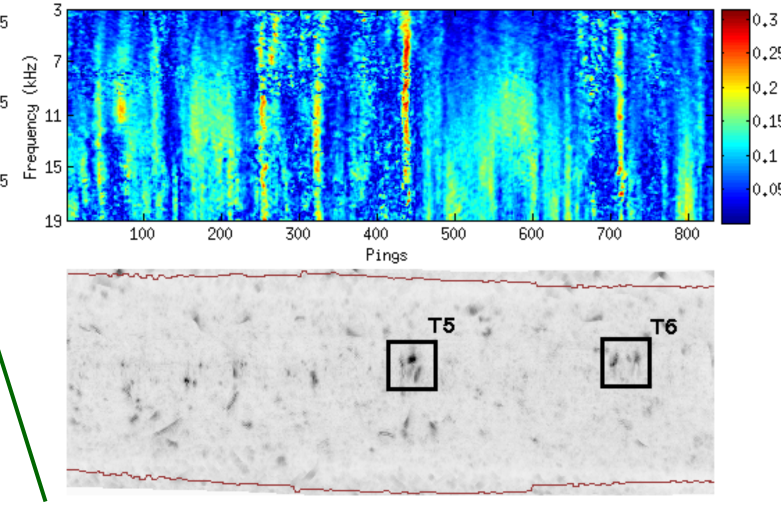
SAS Image Comparison

Additional Runs

Coherence-based SAS-like image

Conventional delay-and-sum SAS image

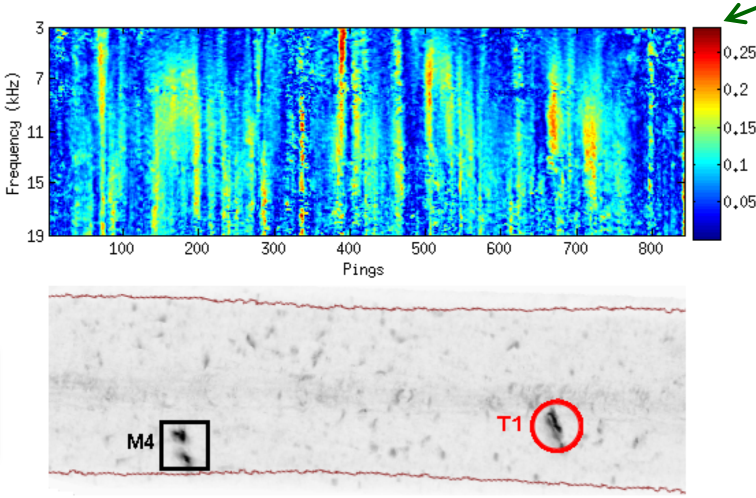


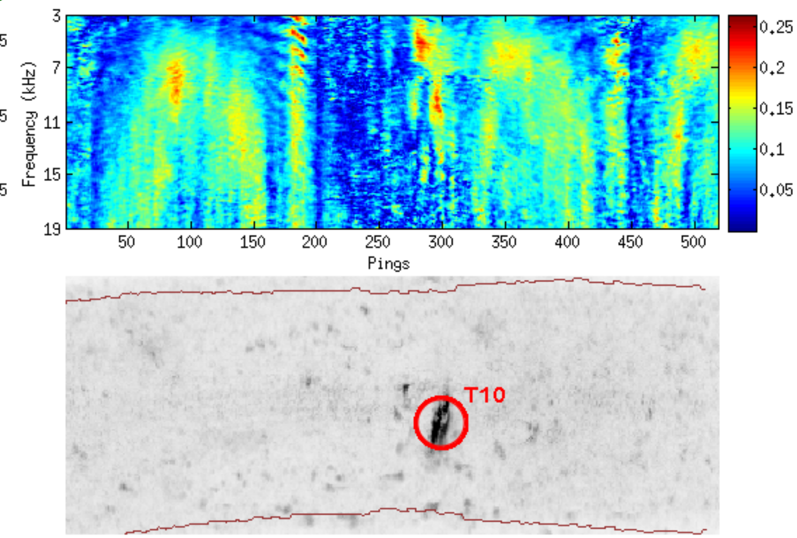


Magnitude of averaged canonical coordinate samples

Ping Window: N = 71

Coordinates samples: L = 5





Targets in red

Non-targets in black

Conclusions

- Coherence-based features (CFS and CTD) are robust to changes in vehicle altitude and many types of environmental conditions
- When using the CFS features, higher classification rates and fewer false alarms are generally obtained compared to the CTD method
    - Attributed to the ability of the CFS method to produce theoretically and intuitively more meaningful coherence patterns from the frequency subbands of two sonar pings
- Multi-aspect classification can be used to further improve classification performance
- Conventional SAS images contain information useful for object detection and across track and along track localization
- Coherence-based SAS-like images offer target detection, classification, and along track localization without requiring estimation of platform motion

Future Work

- Conduct an in-depth analysis relating CFS dominant canonical correlation patterns to specific object types and their properties
- Explore different options for normalizing feature vectors in the case where features from different runs are incompatible with each other
- Develop a solid theoretical foundation for the coherence-based blind SAS processing algorithm
- Investigate the applicability of the proposed methods to other detection/classification studies such as problems in signal processing, communications, radar, sensor fusion, etc.

Questions?

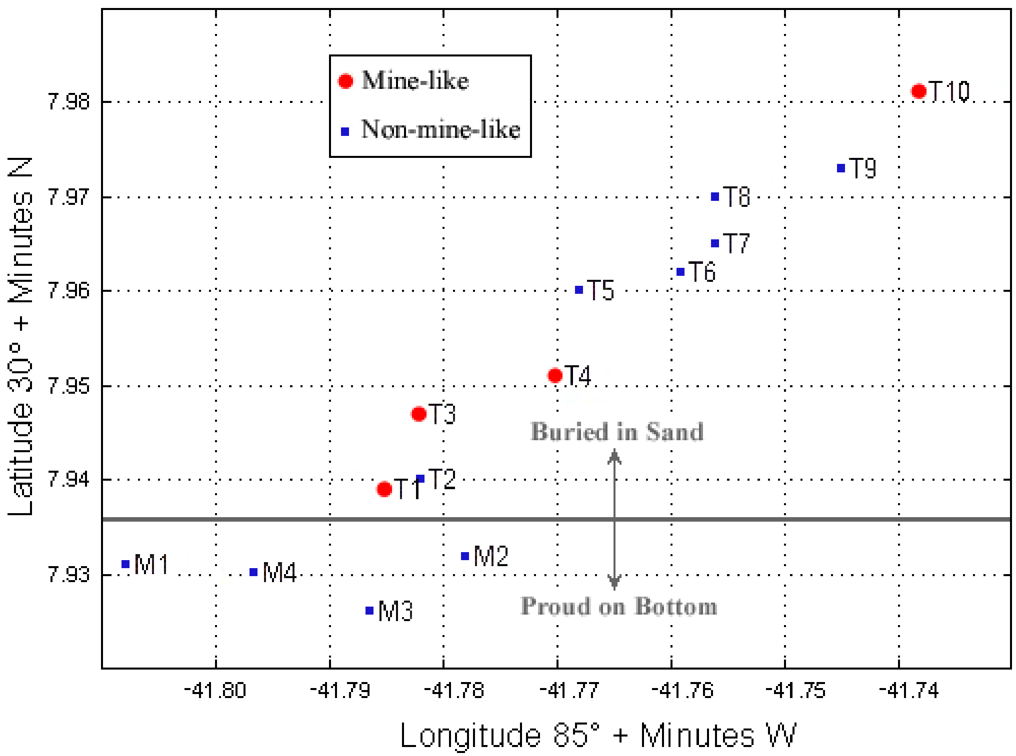
Additional Information

- Literature Review
- Davis Point Object Descriptions
- BOSS UUV Paths
- Subband Decomposition
- Yankee Feature Normalization
- CMAC Details
- DF Details
- Absolute Classification Rates
- Multi-Aspect Classifier ROC curves
- Additional Results on Entire Runs
- Additional SAS Image Comparison

Literature Review

- **Feature extraction:**
  - [Azimi] Two channel canonical correlation analysis and multi-channel coherence analysis applied to sonar returns in time domain
  - [Intrator, Miklovic] Acoustic color processing
- **Detection/classification:**
  - [Azimi] Hidden Markov Models (HHMs), decision-level fusion, collaborative multi-aspect classifier (CMAC)
  - [Carin] HMMs, wavelet-based feature-level fusion
  - [Sternlicht] Fusion of decisions made using image-based and acoustic-based classifiers
- **Synthetic Aperture Sonar Processing:**
  - [Schock] Conventional delay-and-sum SAS processing with BOSS
  - [Lo, Solomon] Application of many adaptive beamforming algorithms to sonar data

Davis Point Object Descriptions



Buried

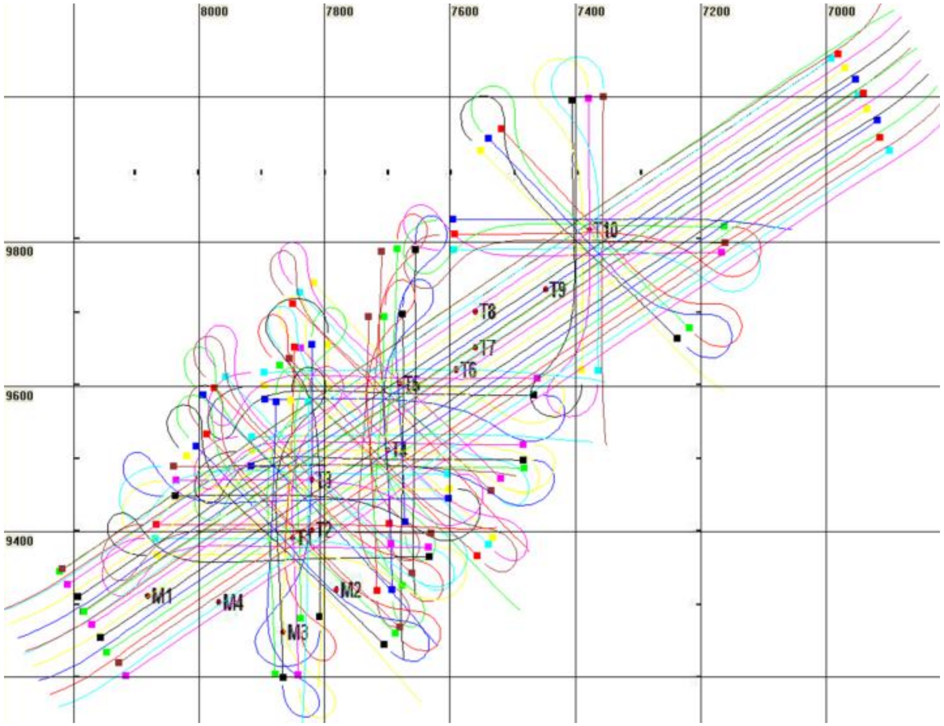
- **T01** SW 6' Bomb-Shaped Marker (18" OD)
- **T02** 20" 81mm Artillery Shell
- **T03** 5.5' Bomb-Shaped Target (11" OD)
- **T04** 6' Iron Cylinder (18" OD)
- **T05** 5' Iron Cylinder (7" OD)
- **T06** 14" Stainless Steel Sphere (with 80 A-m^2 Bar Magnet)
- **T07** 35” 203mm Artillery Shell
- **T08** 14" Stainless Steel Sphere (with 80 A-m^2 Bar Magnet)
- **T09** 2' Iron Cylinder (6" OD)
- **T10** NE 6' Bomb-Shaped Marker (18" OD)

Proud

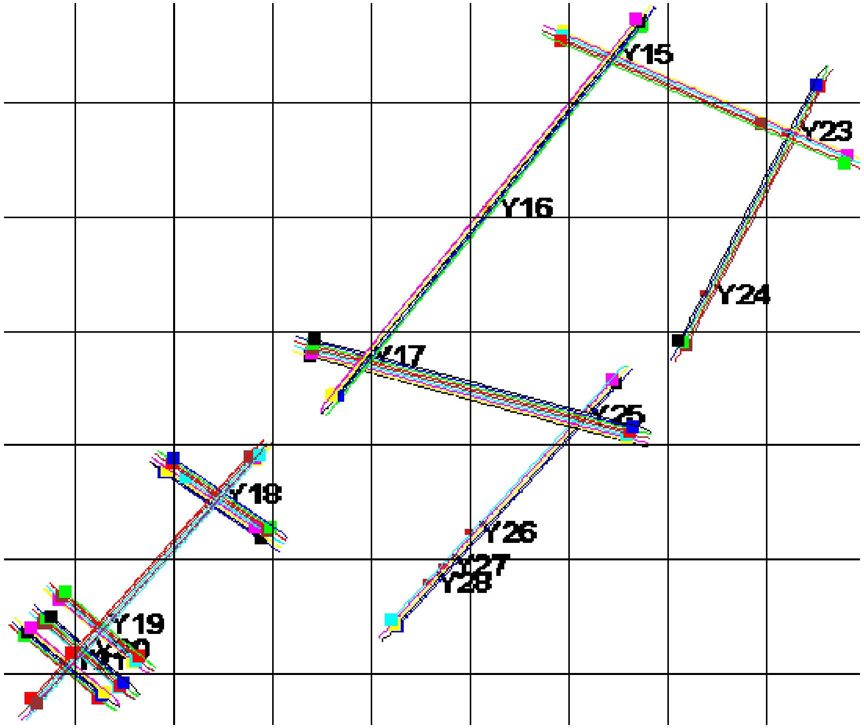
- **M1** 96” Concrete Pipe (18” OD)
- **M2** 72” Concrete Pipe (18” OD)
- **M3** 72” Concrete Pipe (18” OD)
- **M4** 72” Concrete Pipe (18” OD)

BOSS UUV Paths

Davis Point Data Set – March 2007



Yankee Data Set – May/June 2006



Subband Decomposition

Preprocessing
Backup Slides

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- Extract frequency subbands from target impulse response $\hat{\mathbf{h}}_p = \left[\hat{h}_p[0] \ldots \hat{h}_p[N-1]\right]^T$ for subsequent feature extraction
  - **Modulation matrix**: $\boxed{\mathrm{T}_m = \mathrm{diag}(1, W_N^{mL}, W_N^{2mL}, \ldots, W_N^{(N-1)mL})}$, $m \in [0, M-1]$ where $W_N = e^{-j\frac{2\pi}{N}}$
  - **Circular convolution matrix** filters out all but *L* samples:

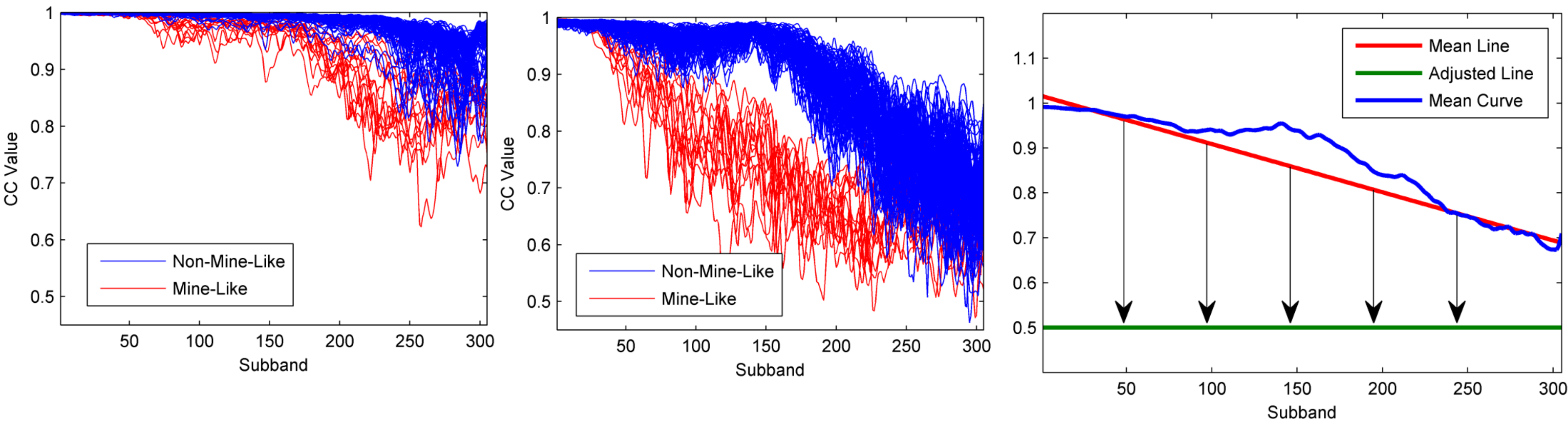
$$\boxed{\mathrm{G}_L = \frac{1}{N}\begin{bmatrix} L & \sum_{k=0}^{L-1} W_N^{-(N-1)k} & \cdots & \sum_{k=0}^{L-1} W_N^{-k} \\ \sum_{k=0}^{L-1} W_N^{-k} & L & \cdots & \sum_{k=0}^{L-1} W_N^{-2k} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{k=0}^{L-1} W_N^{-(N-1)k} & \sum_{k=0}^{L-1} W_N^{-(N-2)k} & \cdots & L \end{bmatrix}}$$

  - **Down-sampling Matrix** (sampling interval *M*):

$$\boxed{\mathrm{S}_M = M\begin{bmatrix} 1 & & \mathbf{0}_{N-1} \\ \mathbf{0}_M & 1 & \mathbf{0}_{N-M-1} \\ \mathbf{0}_{2M} & 1 & \mathbf{0}_{N-2M-1} \\ \vdots & \vdots & \vdots \end{bmatrix}}$$

  - *m*th subband: $\mathbf{y}_p^{(m)} = \mathrm{D}_L \mathrm{S}_M \mathrm{G}_L \mathrm{T}_m \hat{\mathbf{h}}_p$, where D_L is the *L* x *L* DFT matrix

Yankee Feature Normalization



- Every feature vector from a given run, including empty bottom returns, is modified
- Goal is to modify each feature vector such that the average level of coherence exhibited by features from different runs is similar
- For each of the 305 subbands, a mean value of the dominant canonical correlation samples (each sample is obtained from a different feature vector in the run) is found
- A line is fit to the curve representing the mean of the dominant canonical correlation values using the linear least-squares estimate
- All of the dominant canonical correlation samples in a subband are shifted by the difference between the value of the line fit to the mean curve at that subband, and a horizontal line at a magnitude of 0.5

CMAC Details

- Final decision rule minimizes overall expected cost of misclassification for each agent
- Assume:
  - Features are conditionally independent given class C_k: $p(\mathbf{x}_1, \ldots, \mathbf{x}_N | C_k) = \prod_{i=1}^{N} p(\mathbf{x}_i | C_k)$
  - Local preliminary decision made using: $u_i = \gamma_i(\mathbf{x}_i)$
  - Final decision made at each agent using: $u_{fi} = \gamma_{fi}(\mathbf{x}_i, \mathbf{u}_{ir})$
  - Cost of making incorrect decision greater than cost of making correct decision:

$$J_{m=n\ k} \geq J_{m=k\ k}, \quad n \in \{0, 1\}$$

  - Final decision more likely to agree with preliminary decision than disagree:

$$p(|u_{fi} - u_l| \leq \epsilon | \mathbf{u}_{ir}, \mathbf{x}_i) \geq p(|u_{fi} - u_l| > \epsilon | \mathbf{u}_{ir}, \mathbf{x}_i), i, l \in [1, N]; l \neq i,$$

- Solving $\mathrm{Min}\{E[J\{\gamma_{fi}(\mathbf{x}_i, \mathbf{u}_{ir}), C_k\}] = J_{ik}\}$ subject to the above yields:

$$\frac{p(\mathbf{x}_i|C_1)}{p(\mathbf{x}_i|C_0)} \underset{u_{fi}=0}{\overset{u_{fi}=1}{\gtrless}} \frac{P(C_0) \prod_{j=1, j\neq i}^{N} p(u_j|C_0)\,[J_{10} - J_{00}]}{P(C_1) \prod_{j=1, j\neq i}^{N} p(u_j|C_1)\,[J_{01} - J_{11}]}$$

DF Details

DF Description
Backup Slides

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- Final decision rule derived from likelihood ratio test given by:

$$u_{fi} = \Lambda(\mathbf{x}_i) = \frac{p(C_1|\mathbf{x}_i, \mathbf{u}_{if})}{p(C_0|\mathbf{x}_i, \mathbf{u}_{if})} = \frac{p(\mathbf{x}_i, \mathbf{u}_{if}|C_1)P(C_1)}{p(\mathbf{x}_i, \mathbf{u}_{if}|C_0)P(C_0)}$$

- Assume previous decisions and $\mathbf{x}_i$ are conditionally independent:

$$p(\mathbf{x}_i, \mathbf{u}_{if}|C_k) = p(\mathbf{x}_i|C_k) \prod_{m=1}^{M} p(u_{f,i-m}|C_k)$$

- Likelihood ratio can be written as:

$$u_{fi} = \frac{P(C_1)p(\mathbf{x}_i|C_1) \prod_{m=1}^{M} p(u_{f,i-m}|C_1)}{P(C_0)p(\mathbf{x}_i|C_0) \prod_{m=1}^{M} p(u_{f,i-m}|C_0)} = \frac{P(C_0)^M p(C_1|\mathbf{x}_i) \prod_{m=1}^{M} p(C_1|u_{f,i-m})}{P(C_1)^M p(C_0|\mathbf{x}_i) \prod_{m=1}^{M} p(C_0|u_{f,i-m})}$$

Absolute Classification Rates

SA Results
Backup Slides

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Single-Aspect: Davis Point Data Set

	Validation	Testing 1	Testing 2
CFS Features	92.0%	92.1%	89.3%
CTD Features	88.0%	86.1%	78.6%
Improvement	**+4.0%**	**+6.0%**	**+10.7%**

Single-Aspect: Yankee Data Set

	Validation	Testing 1	Testing 2
CFS Features	93.2%	93.2%	87.3%
CTD Features	100.0%	81.4%	74.5%
Improvement	**-6.8%**	**+11.8%**	**+12.8%**

Multi-Aspect: Davis Point Data Set

	Validation	Testing 1	Testing 2
CMAC	**96.0%**	**98.0%**	**93.8%**
DF	92.0%	96.0%	92.0%
NDLF	94.0%	91.1%	92.0%

Multi-Aspect: Yankee Data Set

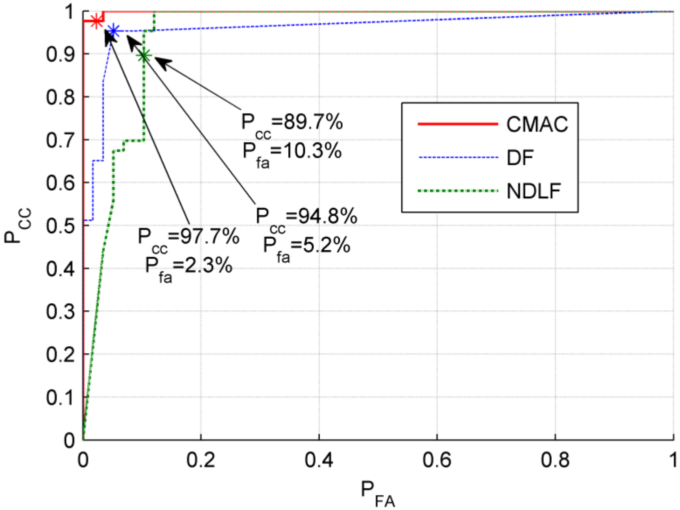
	Validation	Testing 1	Testing 2
CMAC	**100.0%**	**96.6%**	**94.1%**
DF	97.7%	94.9%	91.2%
NDLF	**100.0%**	94.9%	91.2%

Additional Information:

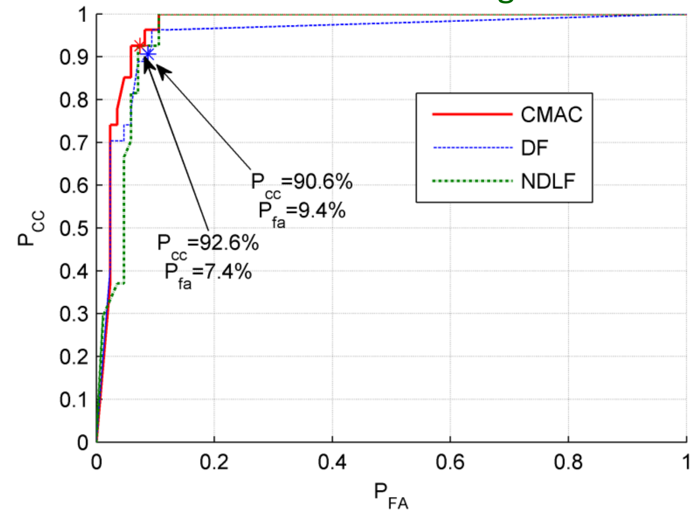
Multi-Aspect Classifier ROC Curves

MA Results
Backup Slides

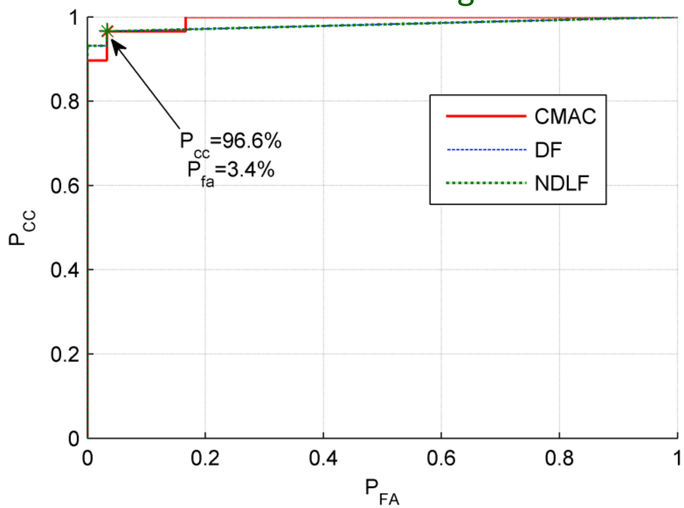
Davis Point Testing 1



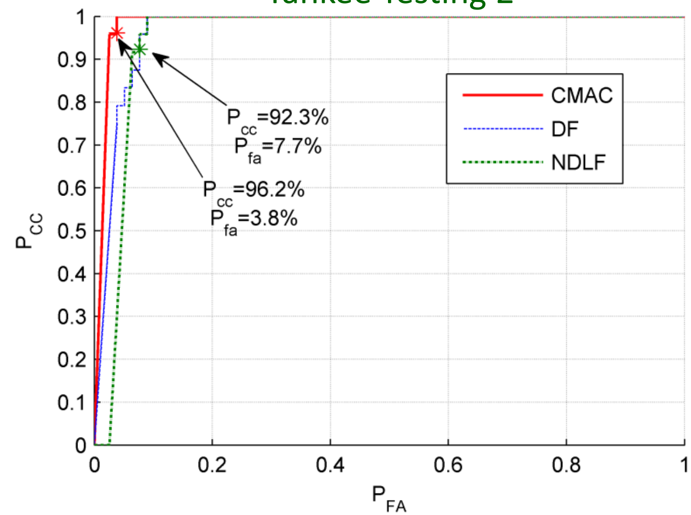
Davis Point Testing 2



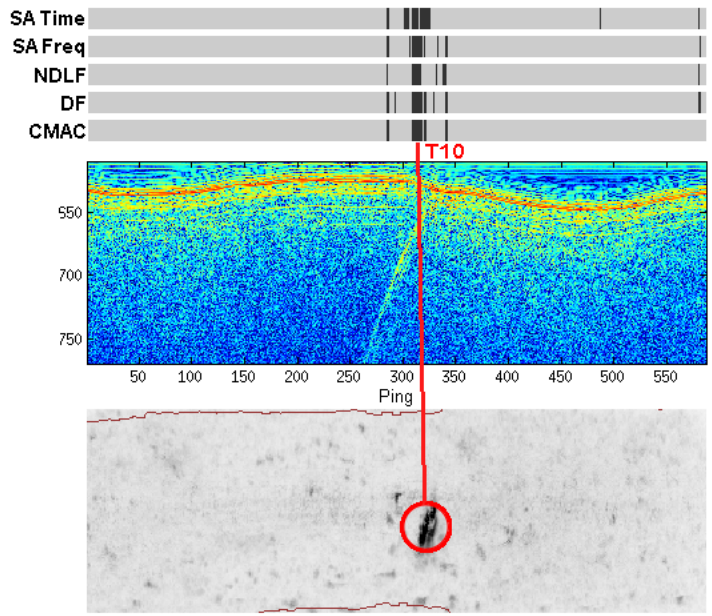
Yankee Testing 1

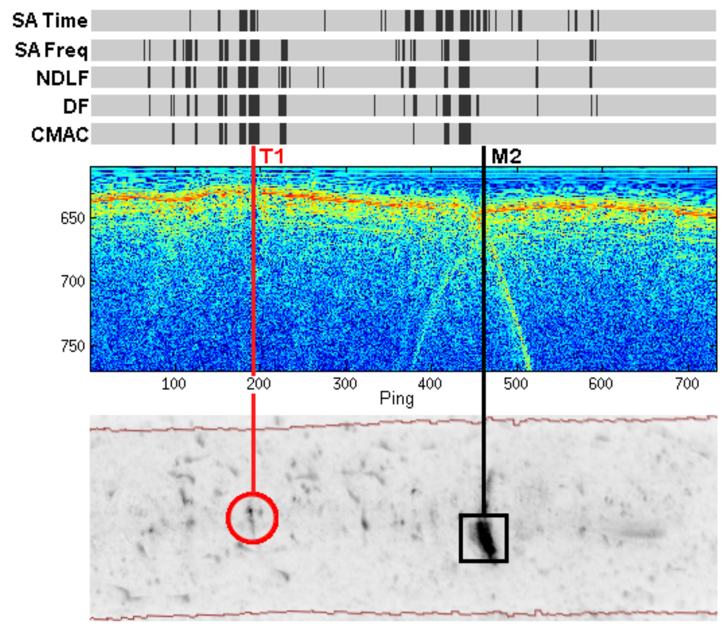


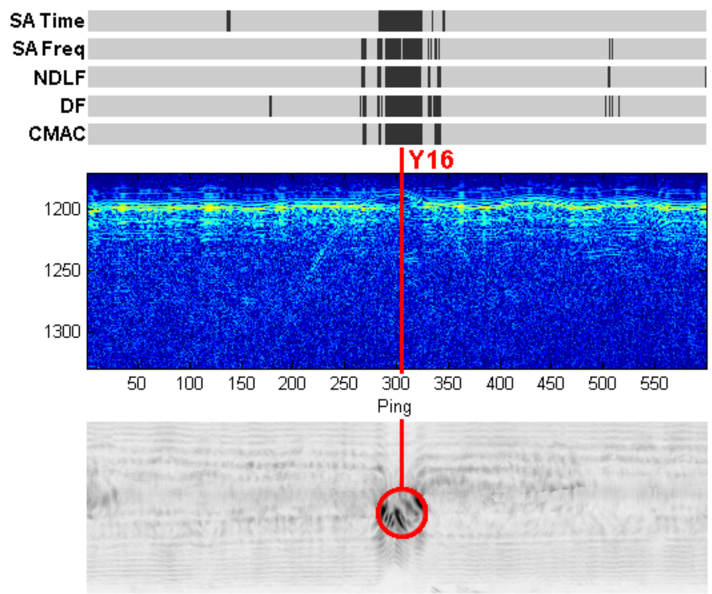
Yankee Testing 2

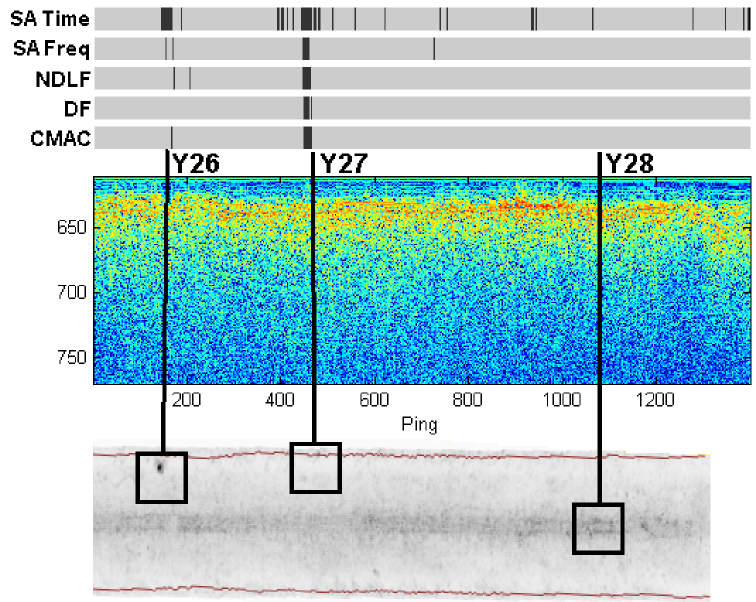


Additional Results on Entire Runs









Additional SAS Image Comparison

Original Runs
Backup Slides