Multi-Platform Target Detection using Multi-Channel Coherence Analysis and Robustness to the Effects of Disparity

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Motivations & Goals

Motivations:

- ✓ The development of an underwater target detection and classification system that can operate with multiple disparate sensing systems poses many technical challenges.
- ✓ Target discrimination based upon individual sensory data together with a decision-level fusion leads to incomplete, degraded, or locally-biased decisions and an unacceptable overall performance at the fusion center.
- ✓ Detection in the Multi-Channel Coherence Analysis (MCA) framework allows one to simultaneously detect the presence of signals among multiple disparate platforms forgoing the hazards of decision or feature-level fusion techniques based on individual sensory data.

Goals:

- ✓ Develop a coherence-based detection method for multiple disparate platforms using the (MCA) framework.
- ✓ Cast the MCA framework in the Neyman-Pearson theory of binary hypothesis testing for Gaussian random vectors and develop new expressions for the log-likelihood ratio and J-divergence measure.
- ✓ Gauge the performance of the MCA-based detector to variability that may occur in any disparate, multi-platform detection problem using a dataset of synthetically generated sonar snippets.

Multi-Channel Coherence Analysis – An Overview

Consider N channels $\mathbf{x}_j \in \mathbb{R}^{d_j \times 1} \quad j = 1, 2, \ldots, N$ forming the composite data vector: $\mathbf{z} = \left[\mathbf{x}_1^H \mathbf{x}_2^H \cdots \mathbf{x}_N^H\right]^H$

Composite covariance matrix: $R_{\mathbf{zz}} = E\left[\mathbf{z}\mathbf{z}^H\right] = \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1N} \\ R_{21} & R_{22} & \cdots & R_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ R_{N1} & R_{N2} & \cdots & R_{NN} \end{bmatrix}$

Search for the mapping vector: $\mathbf{a}_i = \begin{bmatrix} \boldsymbol{\alpha}_{i,1}^H & \boldsymbol{\alpha}_{i,2}^H & \cdots & \boldsymbol{\alpha}_{i,N}^H \end{bmatrix}^H$
that produces the *i*th multi-channel coordinate for every channel: $\mathbf{v}_i = \begin{bmatrix} \mathbf{x}_1^H \boldsymbol{\alpha}_{i,1} & \mathbf{x}_2^H \boldsymbol{\alpha}_{i,2} & \cdots & \mathbf{x}_N^H \boldsymbol{\alpha}_{i,N} \end{bmatrix}^H$
by solving the following maximization problem:

$$\mathbf{a}_i = \arg\max_{\mathbf{a}_i} \sum_{j=1}^{N} \sum_{k=1}^{N} \boldsymbol{\alpha}_{i,j}^H R_{jk} \boldsymbol{\alpha}_{i,k} \text{ subject to the constraint } \sum_{j=1}^{N} \boldsymbol{\alpha}_{i,j}^H R_{jj} \boldsymbol{\alpha}_{i,j} = 1$$

MCA correlations, Λ, and mapping matrix, A, can be found by solving the generalized eigenvalue problem: $R_{\mathbf{zz}} A = D A \Lambda$

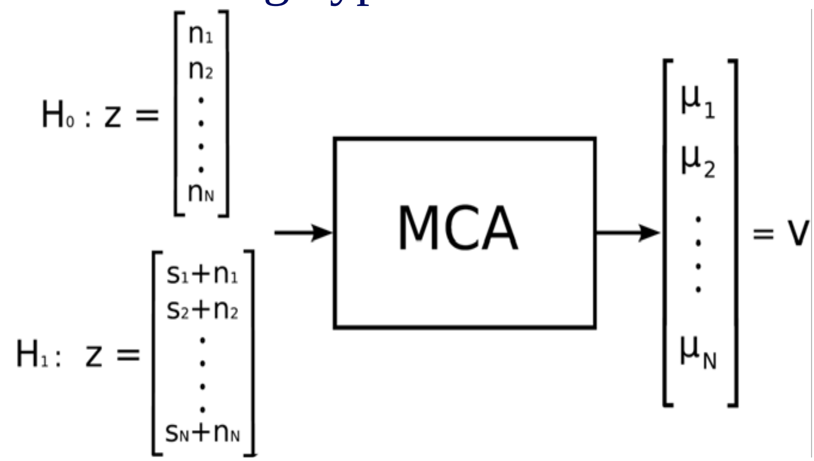
where: $D = \mathrm{diag}\left(R_{11}, R_{22}, \ldots, R_{NN}\right)$

The linear mapping function $A : \mathbb{R}^d \rightarrow \mathbb{R}^d$ with $d = d_1 + \ldots + d_N$ corresponds to a rotation of the coordinate system giving one a more meaningful interpretation of the coherent information shared among all channels. When implementing detection, only the dominant $r = min(d_j)$ coordinates are used as they contain the majority of this information

MCA Detection

To perform coherence-based target detection using N disparate sonar platforms, we will consider a standard signal-plus-noise model and construct the following hypothesis test:

$$H_0 : \mathbf{z} = \begin{bmatrix} \mathbf{n}_1 \\ \mathbf{n}_2 \\ \vdots \\ \mathbf{n}_N \end{bmatrix} \quad \text{vs.} \quad H_1 : \mathbf{z} = \begin{bmatrix} \mathbf{s}_1 + \mathbf{n}_1 \\ \mathbf{s}_2 + \mathbf{n}_2 \\ \vdots \\ \mathbf{s}_N + \mathbf{n}_N \end{bmatrix}$$



Under H_0 the two covariance matrices needed for MCA analysis become: $R_{\mathbf{z}\mathbf{z}_0} = D_0 = \text{diag}\left(R_{\mathbf{n}_1}, R_{\mathbf{n}_2}, \ldots, R_{\mathbf{n}_N}\right)$

While under H_1 they become:

$$R_{\mathbf{z}\mathbf{z}_1} = \begin{bmatrix} R_{\mathbf{s}_{11}} + R_{\mathbf{n}_1} & R_{\mathbf{s}_{12}} & \cdots & R_{\mathbf{s}_{1N}} \\ R_{\mathbf{s}_{21}} & R_{\mathbf{s}_{22}} + R_{\mathbf{n}_2} & \cdots & R_{\mathbf{s}_{2N}} \\ \vdots & \vdots & \ddots & \vdots \\ R_{\mathbf{s}_{N1}} & R_{\mathbf{s}_{N2}} & \cdots & R_{\mathbf{s}_{NN}} + R_{\mathbf{n}_N} \end{bmatrix}$$ and $D_1 = \text{diag}\left(R_{\mathbf{s}_{11}} + R_{\mathbf{n}_1}, R_{\mathbf{s}_{22}} + R_{\mathbf{n}_2}, \ldots, R_{\mathbf{s}_{NN}} + R_{\mathbf{n}_{NN}}\right)$

Implementing the optimum detector in this framework results in the following log-likelihood ratio (LLR):

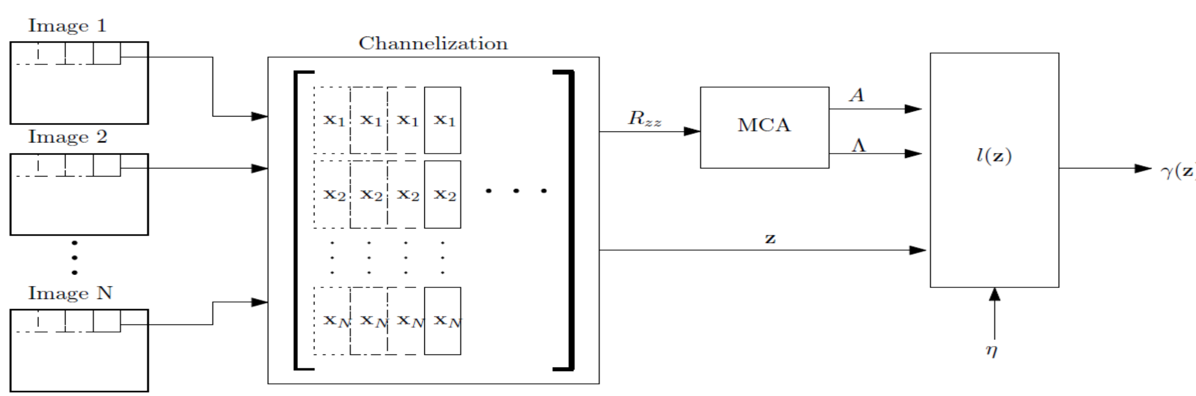
$$l(\mathbf{z}) = \ln\left[\frac{p\left(\mathbf{z}|H_1\right)}{p\left(\mathbf{z}|H_0\right)}\right] = \mathbf{z}A\left(I - \Lambda^{-1}\right)A^H\mathbf{z}$$

and J-divergence (a measure of the amount of discriminatory information for detection):

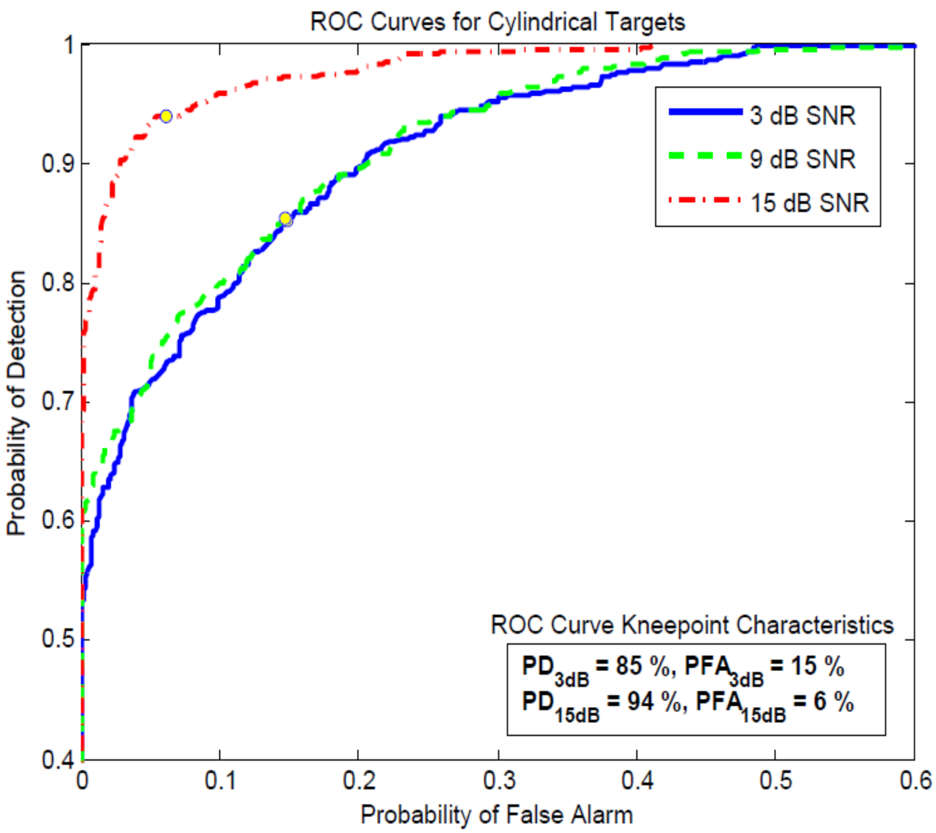
$$J = E_{H_1}\left[l(\mathbf{z})\right] - E_{H_0}\left[l(\mathbf{z})\right] = \sum_{i=1}^{r}\left(-2 + \lambda_i + \lambda_i^{-1}\right)$$

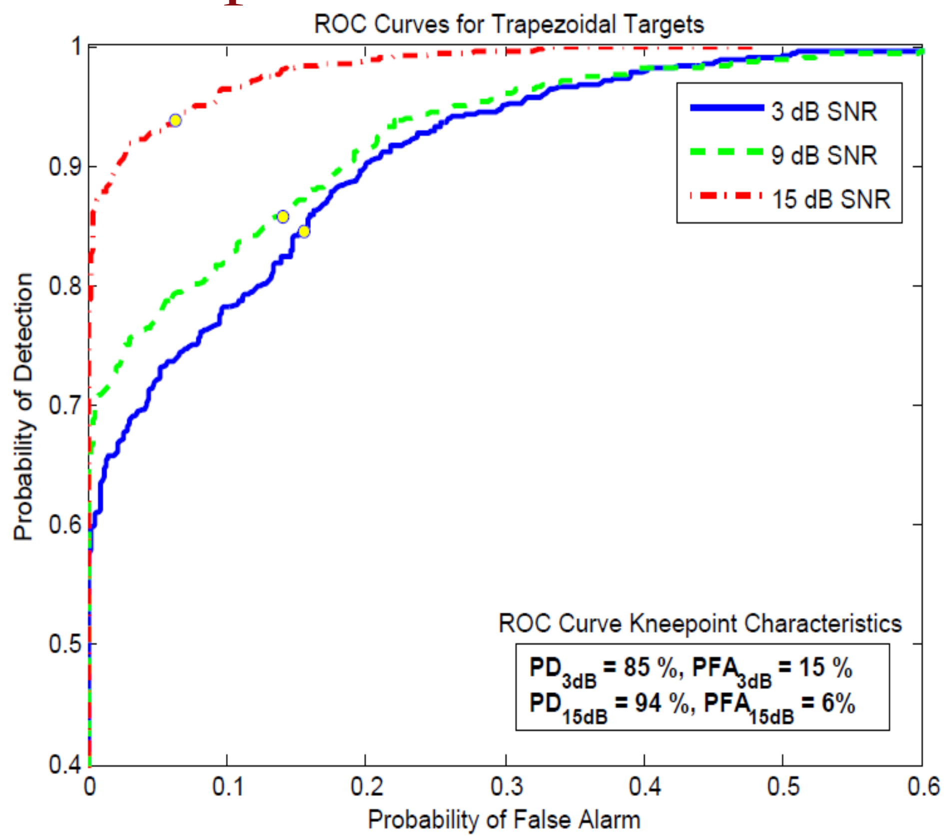
Sonar Imagery Database and Preprocessing

- ✓ Database (from NSWC-PC) contains synthetically generated sonar snippets of both targets and non-targets of different geometrical shapes.
- ✓ Sonar snippets generated wrt several variables including
  - ✓ Image Resolution: 1*in* and 3*in*
  - ✓ SNR: 0*dB* to 15*dB* in increments of 3*dB*
  - ✓ Range: 10*m* to 120*m* in increments of 1*m*
  - ✓ Aspect Angle: 0° to 360° in increments of 1°
- ✓ The subset of 1610 target snippets (hypothesis H_1) was partitioned on the basis of target type (138 cone-type, 736 cylinder-type, 736 trapezoidal-type) while background snippets were used to represent hypothesis H_0.
- ✓ When performing detection, each of the *N* images is partitioned into blocks of size dependent on the image resolution.
- ✓ Each block from all snippets is channelized and forms a realization of the composite data vector, **z**.
- ✓ The LLR is then computed for all blocks within the snippets to yield final detection decision based upon Majority Rule.



Dual Platform, Resolution-Disparate Detection





- ✓ Two-channel detection problem was constructed where each channel in the MCA consisted of snippets of targets of the same type at the same range, aspect angle, and SNR; whereas the sonar resolution was different , i.e. one high resolution (1*in*) and the other lower resolution (3*in*).
- ✓ Results partitioned on the basis of target type and SNR indicate a non-linear increase in performance as a function of SNR for cylindrical and trapezoidal target types.

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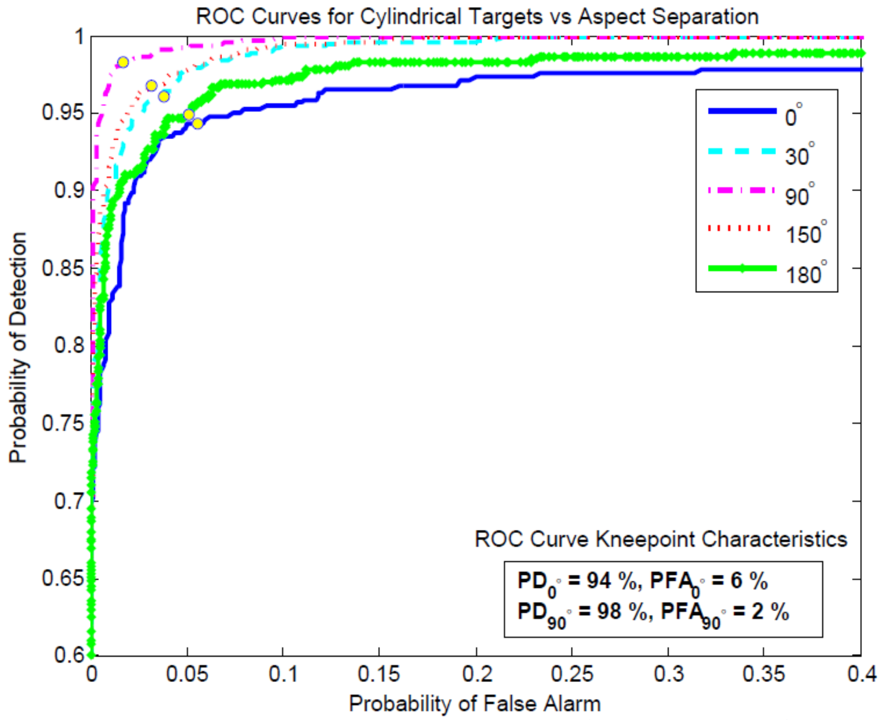
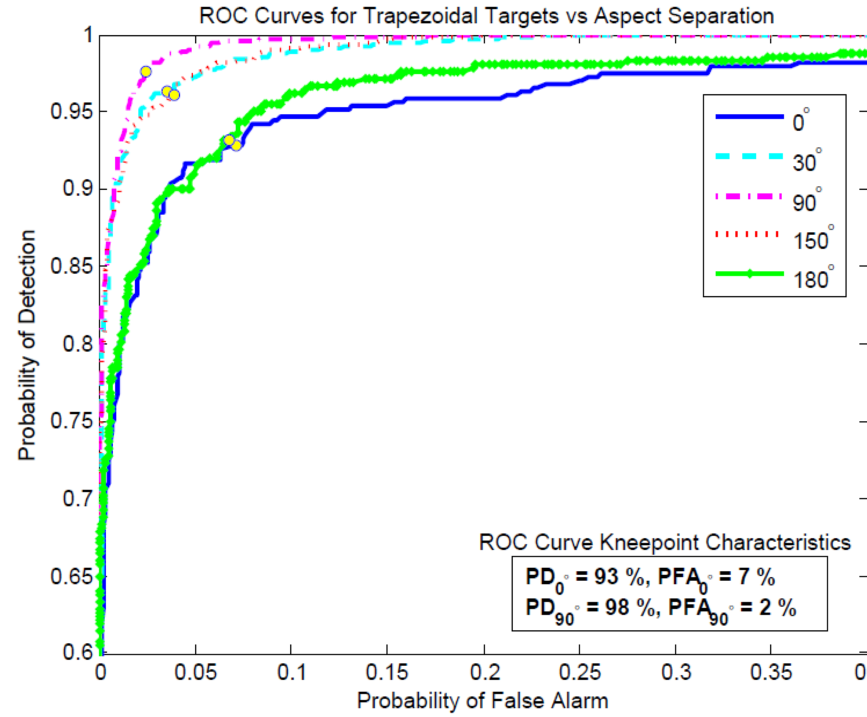
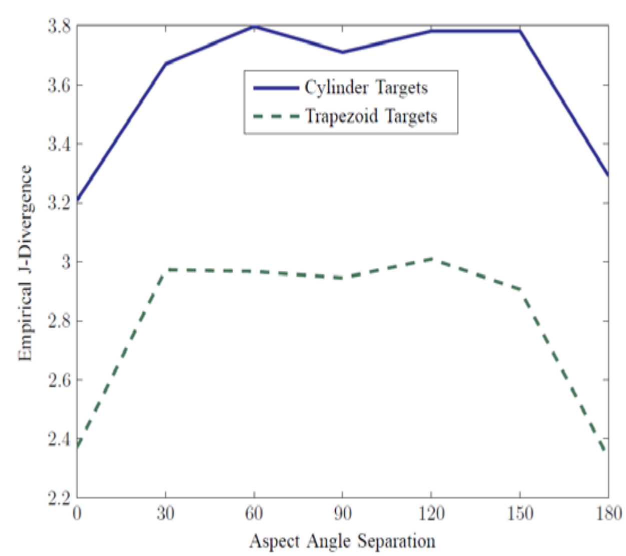
Dual Platform, Aspect Separation-Disparate Detection





- ✓ Here, the two channels consisted of snippets of targets of the same type at the same resolution (1*in*), at ranges with ±1*m*, and at an identical SNR (9*dB*); while the separation in aspect angle was within the range of some angle, θ, which was varied from 0° to 180° in increments of 30°.
- ✓ Results partitioned on the basis of target type and at various values of θ seem to indicate that the detector is fairly robust to aspect angle separation.
- ✓ Empirical J-divergence (with expectation taken over all pairs of images that match the criteria) reflects these results as $J_{max} - J_{min} \approx 0.6$ for both target types.



Conclusions

- ✓ A novel MCA-based optimum detector is developed for underwater target detection and feature extraction from N-disparate sonar imagery. The method exploits multi-channel coherence in the sonar images.
- ✓ Theoretically, MCA provides the right coordinate system for multi-channel signal detection by finding mapping vectors that maximize the linear relations (coherence) among all the channels
- ✓ The Neyman-Pearson theory for binary hypothesis testing of Gaussian random vectors is then cast in MCA framework by deriving relationships for the log-likelihood ratio and J-divergence.
- ✓ Analysis based on a dataset of synthetically generated sonar snippets indicates robustness to different conditions that may be encountered in any disparate detection problem.
- ✓ Although this study emphasized the dual channel detection problem, a similar study could be conducted using images captured from any number of sonar platforms.