Underwater Target Detection from Multi-Platform Sonar Imagery Using Multi-Channel Coherence Analysis

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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.

Goals:

- ✓ Develop a coherence-based detection method involving multiple disparate platforms using the Multi-Channel Coherence Analysis (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.
- ✓ Detection in the 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.
- ✓ Implement and test this detection method to a data set consisting of a high-frequency (HF) and three broadband (BB) side-looking sonar imagery co-registered over the same region on the sea floor.

Multi-Channel Coherence Analysis – An Overview

Consider N channels $\mathbf{x}_j \in \mathbb{R}^{d_j \times 1}$ $j = 1, 2, \ldots, N$ 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: $R_{\mathbf{zz}} A = D A \Lambda$

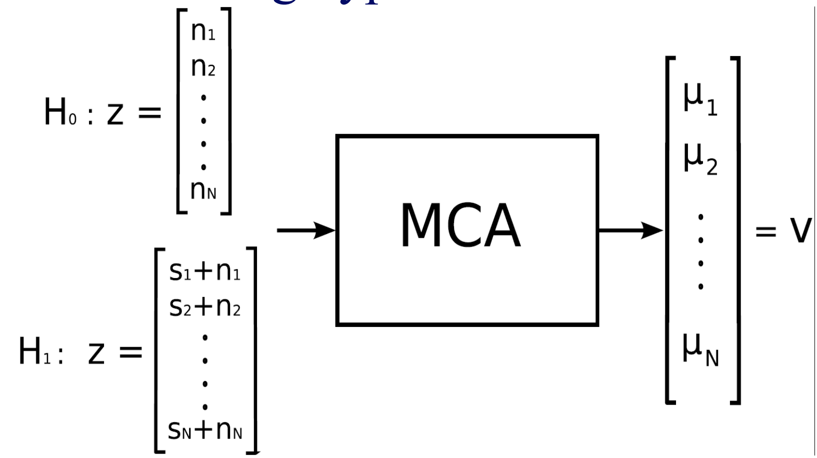
where: $D = \operatorname{diag}\left(R_{11}, R_{22}, \ldots, R_{NN}\right)$

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: $R_{\mathbf{zz}_0} = D_0 = \text{diag}\left(R_{\mathbf{n}_1}, R_{\mathbf{n}_2}, \ldots, R_{\mathbf{n}_N}\right)$

While under H_1 they become:

$$R_{\mathbf{zz}_1} = \begin{bmatrix} R_{\mathbf{s}_{11}} + R_{\mathbf{n}_1} & R_{\mathbf{s}_{12}} & \cdots & R_{\mathbf{s}_{1N}} \\ R_{\mathbf{s}_{21}} & R_{\mathbf{s}_{22}} + R_{\mathbf{n}_2} & \cdots & R_{\mathbf{s}_{2N}} \\ \vdots & \vdots & \ddots & \vdots \\ R_{\mathbf{s}_{N1}} & R_{\mathbf{s}_{N2}} & \cdots & R_{\mathbf{s}_{NN}} + R_{\mathbf{n}_N} \end{bmatrix}$$

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):

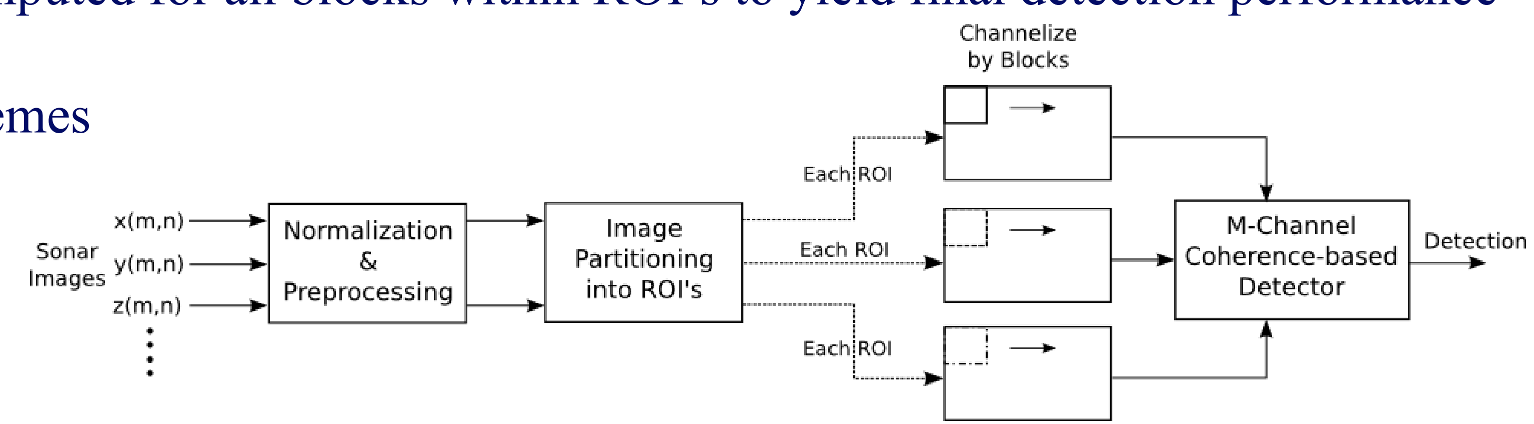
$$l(\mathbf{z}) = \ln\left[\frac{p\left(\mathbf{z}|H_1\right)}{p\left(\mathbf{z}|H_0\right)}\right] = \mathbf{z}A\left(I - \Lambda^{-1}\right)A^H\mathbf{z}$$

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

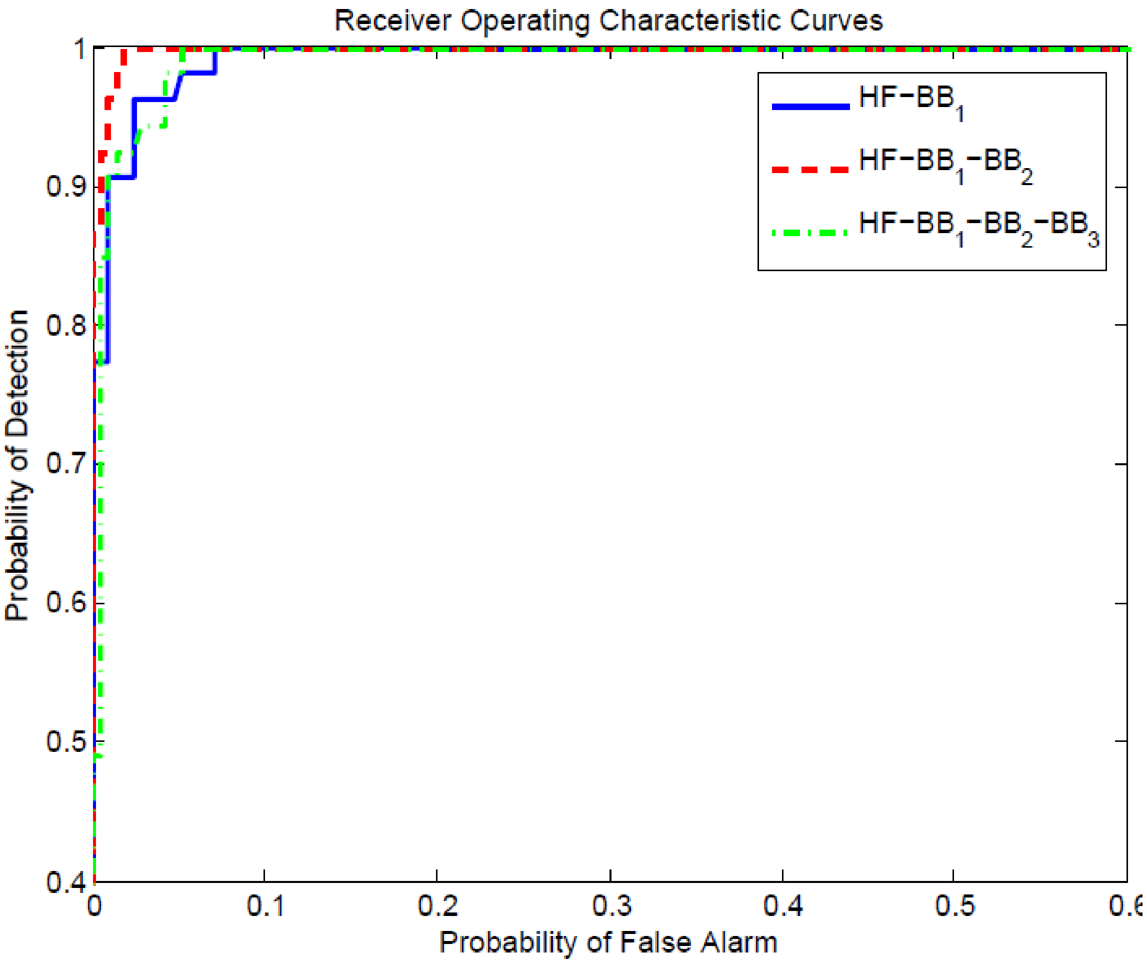
$$J = E_{H_1}\left[l(\mathbf{z})\right] - E_{H_0}\left[l(\mathbf{z})\right] = \sum_{i=1}^{r}\left(-2 + \lambda_i + \lambda_i^{-1}\right)$$

Sonar Imagery Database and Preprocessing

- ✓ Database (from NSWC-PC) contains high-resolution HF (Sonar1) and BB sonar (Sonar 2, 3, & 4) imagery.
- ✓ HF sonar offers good target definition, while BB sonar offers suitable clutter suppression.
- ✓ The HF and BB sonar systems have disparate frequency and spatial resolution characteristics.
- ✓ Database contains 59 co-registered, beamformed (complex-valued) images containing 53 targets at various ranges, cross-ranges, elevations, etc.
- ✓ Each image was then partitioned, with 50% overlap, into ROI's of sizes 72 x 112 for HF and 24 x 224 for BB sonar. The size was determined based on average target size.
- ✓ Each ROI is then partitioned into blocks (6 x 4 for HF) and (2 x 8 for BB's) forming vector (row-wise) **realizations** of the channels.
- ✓ The LLR is then computed for all blocks within ROI's to yield final detection performance (Majority Rule).
- ✓ Three detection schemes performed in this manner: HF-BB1, HF-BB1-BB2, and HF-BB1-BB2-BB3.



MCA Detection Results



Knee Point Characteristics

Sonar #'s	P_D	P_{FA}	J_{Emp}
HF,BB2	96 %	4 %	1.2
HF,BB2,3	98 %	2 %	2.5
HF,BB2,3,4	96 %	4 %	1.7

- ✓ 2-Sensor – Detected 51 Targets / 7.5 FA per image.
- ✓ 3-Sensor – Detected 52 Targets / 8.9 FA per image.
- ✓ 4-Sensor – Detected 52 Targets / 9.3 FA per image.

- ✓ Detection threshold of 10.2 was used for all three scenarios and therefore seems to be fairly robust with respect to the number of channels.
- ✓ Notice a slight decrease in performance going from 3 to 4 sensors as adding the third BB sonar doesn't bring any new information of the miss-detected target and only increases the false alarm rate.

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 ROI's of the sonar images.
- ✓ Theoretically, MCA provides the right coordinate system for multi-channel signal detection by finding mapping vectors that maximize the linear relations among all the channels
- ✓ The Neyman-Pearson theory for binary hypothesis testing of Gaussian random vectors is then cast in MCA framework by providing relationships of the log-likelihood ratio and J-divergence.
- ✓ Experimental results on disparate sonar database demonstrated excellent detection performance for 2- and 3-sonar cases with an average of 8 and 7 false alarms per image, respectively. The 4-sonar case showed diminishing return on detection performance.
- ✓ The targets missed were faint in signature and hard to visually discern in all images hence leading to low coherence.