Statistics-based classification of passive sonar signals

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Penn State Team: Faculty: R. Lee Culver\textsuperscript{1} and Nirmal K. Bose\textsuperscript{2}
Students: Colin W. Jemmott\textsuperscript{3}, Jeremy Joseph\textsuperscript{3}, Brett Bissinger\textsuperscript{2}, Jeff Ballard\textsuperscript{3} and Alex Sell\textsuperscript{3}
\textsuperscript{1}Applied Research Lab, \textsuperscript{2}Department of Electrical Engineering, and \textsuperscript{3}Graduate Program in Acoustics
Penn State University, State College, PA
Contact info: 814 865-3383 rlc5@psu.edu

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Research Goals

• Develop a signal processing structure that exploits environmental knowledge to improve detection and classification while remaining robust to variable and random signal and noise.
• Focus is on passive sonar and frequencies $\leq 1$ kHz.
Statistics-based classification

Sources of received signal variability:
- Variability in the environment
- Source and/or receiver motion
Measuring variation in the ocean volume

Surface float

CTD fins

ASD Sensortecnic towed CTD chain

V-Fin depressor
Measured sound speed variation in the ocean volume

\[
\langle c(r, z) \rangle_r
\]

Average over range:
\[ c(z) \triangleq \langle c(r, z) \rangle_r \]

The anomaly is:
\[ c(r, z) - c(z) \]

\~25 nm west of San Diego August 2002
Received signal amplitude variation due to source motion

- Bottomed horizontal line array @ 200m depth
- Towed source moving at 5 knots transmitting tonal signals

http://www.mpl.ucsd.edu/swellex96/s5.htm
Statistics-based classification

**Talk Outline**
- Previous work
- Likelihood ratio implementations
  - Estimated Ocean Detector
  - High SNR case
- Predicting received signal statistics

**Major point**
- We and others have shown that classifiers work well if the predictions are sufficiently accurate.
- It has not been shown that received signal statistics can be predicted with required accuracy and speed.
Simanin (1990)

  - Question: can the received signal amplitude pdf be used to classify the source => receiver path?
  - Used analytical functions for amplitude pdfs:
    - Unsaturated scattering: log-normal pdf (Flatté et al.)
    - Partially saturated scattering: K distribution (Flatté, Jakeman)
    - Fully saturated scattering: Rayleigh (Flatté et al.)
    - Rough surface scattering: Rayleigh-Rice (Brekhovskikh)
    - pdf parameters must be estimated from environmental data
  - LR classifier, in-water data, achieved ~70% correct classification
Premus (1999)

  – Question: Can scintillation of modal amplitudes can be used to classify source depth?
  – Assumes modal amplitude scintillation is caused by source depth oscillation due to internal or surface waves.
Wagstaff (1998)

- In general, in-water data show that signals from submerged sources vary much less than signals from shallow sources.

• Wagstaff showed that the difference between the average of a signal power series \( P[n] \) and the harmonic mean depends upon the variations.

\[
\text{Avg Pow} = \frac{1}{N} \sum_{n=1}^{N} P[n]
\]

\[
\text{Harmonic Mean} = \left[ \frac{1}{N} \sum_{n=1}^{N} \frac{1}{P[n]} \right]^{-1}
\]
Wagstaff

Examples

• Example 1: N=3, P[n] = [3 2 4] (small variance)

\[
\text{Avg Pow} \quad \frac{1}{3} \cdot (3 + 2 + 4) = \frac{9}{3} = 3
\]

\[
\text{Harm Mean Power} \quad \frac{1}{3} \cdot \left(\frac{1}{3} + \frac{1}{2} + \frac{1}{4}\right)^{-1} = \frac{13}{36}^{-1} = 2.78
\]

\text{Delta} = 0.22

• Example 2: N=3, P[n] = [1 7 1] (large variance)

\[
\text{Avg Pow} \quad \frac{1}{3} \cdot (1 + 7 + 1) = \frac{9}{3} = 3
\]

\[
\text{Harm Mean Power} \quad \frac{1}{3} \cdot \left(\frac{1}{1} + \frac{1}{7} + \frac{1}{1}\right)^{-1} = \frac{15}{21}^{-1} = 1.4
\]

\text{Delta} = 1.6
Wagstaff Processor

- The processor detects or classifies signals from submerged sources by comparing the harmonic mean with the average power:
  - Small difference => submerged
  - Large difference => noise, clutter
- Empirical threshold

(i.e. frequency)
Statistics-based classification

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Consider observation \( r = s(\theta) + n \). A composite Likelihood Ratio (LR) incorporates statistical knowledge of the random signal parameter \( \theta \):

\[
\Lambda(r) = \frac{p(r \mid H_1)}{p(r \mid H_2)} = \frac{\int_{-\infty}^{\infty} p[r \mid H_1, \theta] p(\theta \mid H_1) d\theta}{\int_{-\infty}^{\infty} p[r \mid H_2, \theta] p(\theta \mid H_2) d\theta}
\]

When the noise is additive, the likelihood function is the pdf of the noise:

\[
p[r \mid H_1, \theta] = p[r - s(\theta) \mid H_1, \theta] = p_n(r - s(\theta) \mid H_1)
\]
Ballard (2009)

Ballard considered Gaussian noise and Gaussian-distributed signal amplitudes, i.e. $\theta = A$. The signals have the same mean but different variances.

$$f(A | H_1) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \exp\left[-\frac{(x-m)^2}{2\sigma_1^2}\right]$$

$$f(A | H_2) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \exp\left[-\frac{(x-m)^2}{2\sigma_2^2}\right]$$

Defining a signal-to-signal ratio:

$$SSR = 10 \log \left( \frac{\sigma_1^2}{\sigma_2^2} \right)$$
Ballard (2009)
Gaussian signal amplitude and noise

Receiver Operating Characteristic (ROC) curves for additive Gaussian noise and Gaussian-distributed received signal amplitudes.
Ballard also considered the case in which the noise pdf belonged to the exponential class:

\[ f_1(r \mid \theta) = K(\theta) \exp\left[ g_1(r, \theta) + B_1(r) \right] \]

Building upon an Estimator-Correlator derivation by Schwartz, the LR receiver is greatly simplified and termed the Estimated Ocean Detector by Sibul.

Estimated Ocean Detector

Noise pdf

Signal Parameter pdf

Signal Parameter pdf

Conditional Moment Function

Received Signal, \( r \)

\( p(\theta \mid H_1) \)

\( p(\theta \mid H_2) \)

\( p(r \mid \theta) \)

\( G_1(r) \)

\( G_2(r) \)

\( B_1(r) \)

\( B_2(r) \)

\( \ln \frac{c_1}{c_2} \)

Statistics-based classification

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Composite LR: High SNR

When the noise is negligibly small, the likelihood function approaches a delta function:

$$p(r \mid H_1, \theta) = p[r - s(\theta) \mid H_1, \theta] \approx \delta[r - s(\theta)]$$

and the Likelihood Ratio becomes the ratio of the predicted signal pdfs:

$$\Lambda(r) \approx \frac{p[s(\theta) \mid H_1]}{p[s(\theta) \mid H_2]}$$

We have made this assumption and applied the composite LR to the 1996 Strait of Gibraltar and Swellex-96 data.

• May 10-18 1996
• Bottomed horizontal line array @ 200m depth
• Towed source moving at 5 knots
• Tonal signals from 100 to 400 Hz, at 9m and 54 m depth


http://www.mpl.ucsd.edu/swellex96/s5.htm
SwellEx-96
Event S5

SwellEx-96
Event S5

The acoustic model doesn’t predict TL time series accurately, but it does predict the statistics well enough to classify the source depth.
SwellEx-96
Event S5

Perfect performance is achieved when all points are fed to the classifier.

Likelihood ratio from acoustic predictions

\[ \Lambda(A) = \frac{p[A|H_1]}{p[A|H_2]} \]

Receiver Operating Characteristic (ROC)

M = # of groups into which points are divided
Other environmental statistics based classifiers

- Brett Bissinger has shown that minimizing Hellinger distance can be used to classify source depth, providing performance equivalent to the LR when the predicted pdfs are accurate, and more robustness to data outliers.

- Colin Jemmott is developing a Bayesian tracking filter that shows promise for localizing moving sources in range and depth using received signal statistics.
Statistics-based classification

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Predicting signal parameter pdfs

• Rough surface PE acoustic propagation model obtained from Rosenberg (APL/JHU); based upon Range-dependent Acoustic Model (RAM), but adds capability for acoustic propagation with time- and spatially-varying rough surface.

• Jeremy Joseph investigated whether this simulation could predict surface interaction effects on signal frequency and amplitude pdfs
Temporal evolution of the surface is obtained by including an exponential term in the integral transform over the random realization (phase) of the wave height spectrum.

\[ \eta(x, t) = \text{Re} \left[ \int_{-\infty}^{\infty} \exp(-iKx) \times \psi(K_x) \exp(2\pi ift) dK_x \right] \]

where \[ f = \frac{1}{2\pi} (gK_x)^{1/2} \]

Transmission loss
U=15 m/s

Received signal amplitude histograms

Methods for acoustic prediction

<table>
<thead>
<tr>
<th>Method</th>
<th>Range dependent?</th>
<th>Execution speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ray tracing</td>
<td>yes</td>
<td>fast</td>
</tr>
<tr>
<td>Wave number integration</td>
<td>no, yes</td>
<td>fast, slow</td>
</tr>
<tr>
<td>Normal mode</td>
<td>no, yes</td>
<td>fast, slow</td>
</tr>
<tr>
<td>PE</td>
<td>yes</td>
<td>slow</td>
</tr>
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</table>
Summary

• Previous work and more recently our work has shown that the statistics of the received signal (e.g. amplitude) can be used in passive sonar to classify source range and depth.

• We have shown that Likelihood Ratio and Minimum Hellinger Distance classifiers are capable of classifying source range and depth using received signal statistics. A Bayesian filter is under development and may also be capable.

• We have not yet shown that signal statistics can be predicted with the accuracy and speed required for a real-time sonar classifier aide. This is the current challenge.