Space-Time Matched-field Depth Estimation for Active Sonar

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Active Matched-field Depth Estimation

OBJECTIVE: To estimate the depth of submerged targets by modeling ping-to-ping changes in complex space-time multipath returns due to shallow-water propagation.

BACKGROUND:

- Active depth estimation would assist in the classification of slow-moving, water-column targets vs. surface ships or bottom features thus reducing the false-alarm rates in active surveillance systems (e.g. ACES, Distant Thunder, activated DADS).
- Acoustic MFP using known source waveforms has been previously investigated by Hermand and Roderick (1993), Yang and Yates (1994), and Bucker (1996) who suggest potential for detection gains as well as localization capability.
- Key problem which plagues both active and passive MFP is that relative amplitudes and phases between modes or rays is very sensitive to uncertainties in the environment and target scattering characteristics.
- In recent radar work, Papazoglou and Krolik (1999) have developed a range-Doppler-domain matched-field altitude estimation method for OTH radar which models changes in unresolved multipath returns without knowledge of the aircraft scattering function.
Depth Estimation for Active Surveillance Sonar

- The spatio-temporal wavefront changes from ping-to-ping due to multipath interference at a receive array from a slowly moving target are range and depth dependent.

- Frequency-wavenumber spectra for series of pings illustrate fading due to changes in eigen-ray phase paths and group delays which can be modeled to facilitate depth estimation.
Active Space-Time Matched-field Depth Estimation

- Multi-ping maximum likelihood depth estimates exploit shape changes in the space-time return without modeling of complex ray amplitudes or target backscatter characteristics.
- Slow fluctuations due to target aspect changes and medium fluctuations are handled using a first-order Markov model for unknown target reflection coefficients.
- Environmental data derived from in situ sound-speed profile measurements. Complex frequency-wavenumber neighborhood of target return identified using a target tracker.
Space-Time Modeling of Active Sonar Returns

- Let $x_n$ contain samples of the complex frequency-wavenumber spectrum of received data in the neighborhood of the $n^{th}$ consecutive ping:

$$x_n = e^{-j\theta} \mathbf{H} \mathbf{a}_{r_n, z_n, v_n} \mathbf{f}_n + \sum_{m=1}^{M} e^{-j\phi_m} \mathbf{H} \mathbf{c}_{r_{m,n}, z_m, b_m, v_m, n} \mathbf{g}_m + \eta_n$$

where $r_n, z_n, v_n$ is the target range, depth, and radial speed, each column of $\mathbf{H}(r_n, z_n, v_n)$ is associated with a two-way ray (or mode) combination, $\mathbf{g}_m$ is the backscatter vector from the $m^{th}$ reverberation patch, and $\eta_n$ is the noise.

- The changing phase path lengths to the sum of $M$ patches decorrelates the reverberation from ping-to-ping at different hypothesized ranges.

- Aspect-dependent target backscatter variations and medium fluctuations can be handled by modeling the target backscatter vector, $\mathbf{d}_n$, as a first-order Gaussian Markov process.

- The absolute bistatic phase paths, $\theta_{rn}, n=1,..,K$ from the sonar platforms to the target for a reference ray (or mode) are assumed to be unknown non-random parameters.
The Geometry of Relative Multipath Delays

- Differential multipath phase delays from ping-to-ping can be modeled using the ray elevation angles and knowledge of target Doppler frequency.

- Between consecutive pings at time $t_k$, the phase change undergone by the $l^{th}$ multipath component is
  \[ \Delta \theta_{l,k} \equiv \frac{\partial \theta_{l,k}}{\partial r_k} \Delta r_k \]
  where $\Delta r_k$ is the change in range.

- Using the ray elevation angles of the each component leads to a simple geometric expression for
  \[ \frac{\partial \theta_{l,k}}{\partial r_k} \Delta r_k = \frac{\omega_k}{c(z)} (\cos \beta_1 + \cos \beta_2) v_r (t_k - t_{k-1}) = \omega_{l,k} (t_k - t_{k-1}) \]
  where $v_r$ is the radial velocity of the target which can be derived from target Doppler.
Multipath Delay Changes on Consecutive Pings

- Plot of relative bistatic multipath delays versus depth illustrate distinctive depth dependence which is not strongly range-dependent between consecutive pings.

- Plot of eigenrays to a particular depth illustrates that relative multipath arrival angles are nearly constant between pings.
Maximum Likelihood Active Matched-field Processing

- Using a Markov model for the time-dependent target reflection coefficients, the maximum likelihood estimate of constant depth, \( z \), is given by:

\[
\arg\max \sum_{k=1}^{K} \log p(x_{o}|z, r_o, v_o) + \log p(x_{k}|x_{k-1}, z, r_k, v_k, \theta_k)
\]

where \( p(x) \) is the multivariate complex Gaussian density function.

- Estimates of \( r_k \) and \( v_k \) can be obtained from the sonar’s tracker output.

- ML estimates of \( \theta_k \) may be solved analytically for this model so that only numerical evaluation of the time-evolving likelihood function accumulation over depth is required.

- Coherent processing requires accurate modeling of ping-to-ping relative multipath phase path changes with range at each hypothesized depth.

- Incoherent MFDE can be achieved by computing \( \arg\max \{ \sum_{k=1}^{K} \log p(x_{k}|z, r_k, v_k) \} \).
Coherent versus Incoherent MFDE

• For $K$ consecutive Gaussian distributed pings, the depth log-likelihood can be expressed as:

$$
\arg \max \left \{ \sum_{k=1}^{K} \log \pi^N |Q_k| - x_k^+ Q_k^{-1} x_k + 2 x_k^+ Q_k^{-1} R_{k,k-1} R_{k-1,k-1}^{-1} x_{k-1} \right \}
$$

where $Q_k = R_{k,k} - R_{k,k-1} R_{k-1,k-1}^{-1} R_{k,k-1}^+$ is the conditional covariance of $x_k$ given $x_{k-1}$ and $R_{k,k-1}, R_{k,k}$ are the respective cross and auto-covariance matrices of $x_{k-1}$ and $x_k$.

• The absolute value of the cross-term captures the depth-dependent fading between pings by modeling the relative phase path changes among the multipath returns.

• In the absence of correlation from ping-to-ping, incoherent MFDE consists of:

$$
\arg \max \{ \sum_{k=1}^{K} \log \pi^N \left| \frac{H(\eta_k,z)}{H(\eta_k,z)} \right|^2 \}
$$

which is a generalization of Bartlett MFP. Normalization by $\sum_{k=1}^{K} tr \{ H(\eta_k,z)^+ H(\eta_k,z) \}$ is required to ensure the power in the model at each hypothesized depth is constant.
MFDE as a One-Dwell Ahead Predictor

- MFDE can be thought of as predicting the complex frequency-wavenumber peak vector on ping \( k \) given data from dwell \( k-1 \) using an depth-dependent model for its shape change.

- The log-likelihood function is essentially a mean-squared error criterion minimizing:
  
  \[
  (x_k - E(x_k|_{x_{k-1}}, z))^\top Q_k^{-1}(x_k - E(x_k|_{x_{k-1}}, z))
  \]

  where \( Q_k(z) \) is the conditional covariance of the prediction under the hypothesized depth \( z \).

- The prediction of dwell \( k \) given dwell \( k-1 \) assumes the phase change undergone by the \( l^{th} \) multipath is
  
  \[
  \frac{\partial \theta_{l,k}}{\partial r_k} dr_k = \frac{\omega_k}{c} (\cos \beta_1 + \cos \beta_2) v_k (t_k - t_{k-1}) = \omega_{l,k} (t_k - t_{k-1})
  \]

  where \( v_r \) is the radial velocity of the target.

- MFDE errors likely to occur when modeled \( \frac{\partial \theta_{l,k}}{\partial r_k} \) does not match the true propagation.
The SWAC-3 Littoral Mediterranean Environment

- Range-dependent Mediterranean environment off Spain from the NATO Shallow-Water Active Classification (SWAC) Test #3, Nov. 1995.

- SWAC-3 scenario with Alliance source-ship and 144-element receive array towed by Sverdrup. Target range between 5 and 12 nmi. at a speed of ~7 knots.
Pulse Fading Characteristics of the SWAC-3 Dataset

- Actual beamformed bistatic ping data illustrating pulse fading from a 1 min. PRI, 4-second ping sequence at 720 Hz off a 7 knot, ~7 nmi. target at 50 m. depth from SWAC-3 Run Bravo.

(SWAC-3 Nov 95 Data Processed by Jim Alsup, SPAWAR)

- Simulated SWAC-3 Run Bravo data illustrating features statistically similar to fluctuations seen in real data.

(SWAC3 environment: Range sequence = [10 km, 20 km, 30 km], SNR = 20 dB, Target Depth 20 m, Platform Depth 70 m)
Coherent Space-Time MFDE Simulation Results

- Histogram of coherent space-time bistatic MFDE depth errors for a target at 50 m. depth in ~75 m. range-varying bathymetry at 15 SNR (blue) and 20 dB SNR (red).

- Example time-evolving depth log-likelihood function using simulated bistatic returns for the SWAC-3 target at 50 m. depth.
Beacon Signal from the SWAC-3 Mediterranean Dataset

- Raw hydrophone data containing a single 0.5 second duration linear FM beacon signal sweeping from 395 to 400 Hz.

- Beacon signal from a single hydrophone after filtering to remove tow-ship noise.
Real SWAC-3 Space-Time MFDE Results

- Actual time-evolving depth log-likelihood function using 16 pings of beacon data from the SWAC-3 target moving from a range of 14 to 17 km. and bearing of 18 to 15 degree at 50 m. depth.

- Time-evolving depth log-likelihood for degraded SWAC-3 beacon data with 20 dB of pseudo-random noise added to the original data.

- Depth estimation accuracy to within 1 meter of ground-truth achieved for both original and degraded real data was obtained without optimization of the environmental model.
Conclusions

• Depth estimation could facilitate classification of slow-moving, water-column targets vs. surface ships or bottom features thus reducing the false-alarm rates in active surveillance systems.

• Space-time matched-field depth estimation (MFDE) for active sonar successfully transitioned from delay-Doppler matched-altitude estimation in OTH HF radar.

• Unlike traditional MFP techniques, MFDE exploits complex shape changes in the space-time return without modeling of complex ray amplitudes or target backscatter characteristics.

• Space-time MFDE demonstrated with both simulated bistatic and real beacon data collected during the littoral Mediterranean SWAC-3 experiment in November, 1995.

• Simulation results suggest estimation accuracy to within 20% of the water column at SNR’s as low as 15 dB may be possible.

• Further work is required to study MFDE performance using real bistatic or multistatic returns in highly cluttered environments.