Detection and Tracking with Environmental Uncertainty: Multi-static Active Systems

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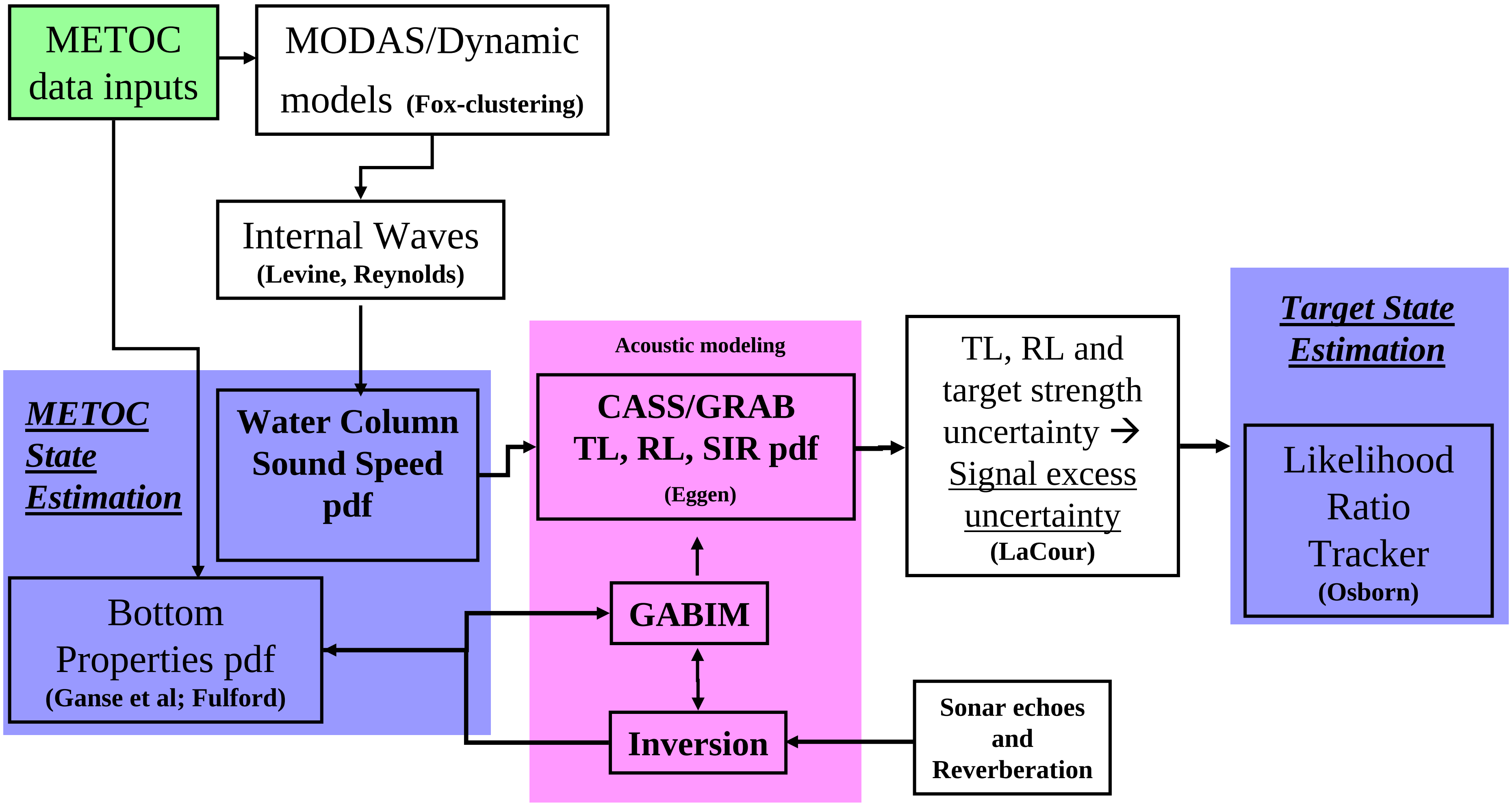
Presentation Outline

- Global Architecture View
  - System Architecture
  - Inputs to Detection and Tracking System
- Description of Likelihood Ratio Tracking
  - Likelihood Ratio Detection and Tracking
  - Modeling Signal Excess
  - Uncertainty and Variability
  - Using SE in Detection and Tracking
- Examples
- Conclusions

System Architecture



Inputs to Detection and Tracking System

- TS – Target Strength
  - **mean TS level**
    - as a function of the bistatic angles for appropriate frequency band
  - **characterization of variability** (i.e. ping-to-ping fluctuation)
  - **characterization of uncertainty** (in mean levels)

- SL / RL / TL – Source Level, Reverberation, and Transmission Loss
  - **mean RL/TL curve(s)**
    - (one or more) averaged over processes whose characteristic time-scale is < operation duration (e.g. internal waves, stochastic processes)
  - **characterization of variability** (i.e. ping-to-ping fluctuation)
    - due to processes whose characteristic time-scale is < operation duration**
  - **characterization of uncertainty** (in mean levels)
    - from processes whose time-scale is > operation duration (e.g. SSP, bottom type)

- NL / DT

- Sensor Measurements

*** assumes range dependent environment**

**** currently reduced to Gaussian independent of state, but this is not a fundamental limitation of the tracker**

Likelihood Ratio Detection and Tracking

- Tracking
  - Assumes target is present
  - Uses only sensor responses that are above threshold
  - Uses these responses to estimate state of target
- Likelihood Ratio Detection and Tracking (LRT)
  - Does not assume target present
  - Uses below threshold sensor responses
  - Determines
    - Whether target present
    - Target state if present
  - Bayesian form of Track-Before-Detect (TBD)

Mathematical Formalism for LRT

- Same as Bayesian tracking except
  - We extend the state space $\boldsymbol{S}$ by adding the null state ϕ to represent the possibility that no target is present in the area of interest.
- We let $S^{+} = S \cup \phi$ be this extended state space.
- We assume there is at most one target in the region so that

$$p(0,\phi) + \int_{S} p(0,s)\,ds = 1$$

- We define the cumulative likelihood ratio as

$$\Lambda(t,s) = \frac{p(t,s)}{p(t,\phi)} = \frac{\mathbf{Pr}\{X(t) = s \mid \textbf{Observations to time } t\}}{\mathbf{Pr}\{X(t) = \phi \mid \textbf{Observations to time } t\}}$$

Mathematical Formalism Continued

- Measurement likelihood ratio for the observation $Y_k = y$

$$\mathrm{L}_k(y \mid s) = \frac{L_k(y \mid s)}{L_k(y \mid f)} = \frac{\mathbf{Pr}\{Y_k = y \mid X(t) = s\}}{\mathbf{Pr}\{Y_k = y \mid X(t) = f\}}$$

- This is the ratio of the likelihood of obtaining the observation $Y_k = y$ given target present at $\boldsymbol{s}$ to the likelihood of obtaining the observation given no target present.

Simplified Likelihood Ratio Recursion

(Initial odds ratio) $\Lambda(0,s) = \dfrac{p(0,s)}{p(0,\phi)}$ for $s \in S$

For $k \geq 1$ and $s \in S$,

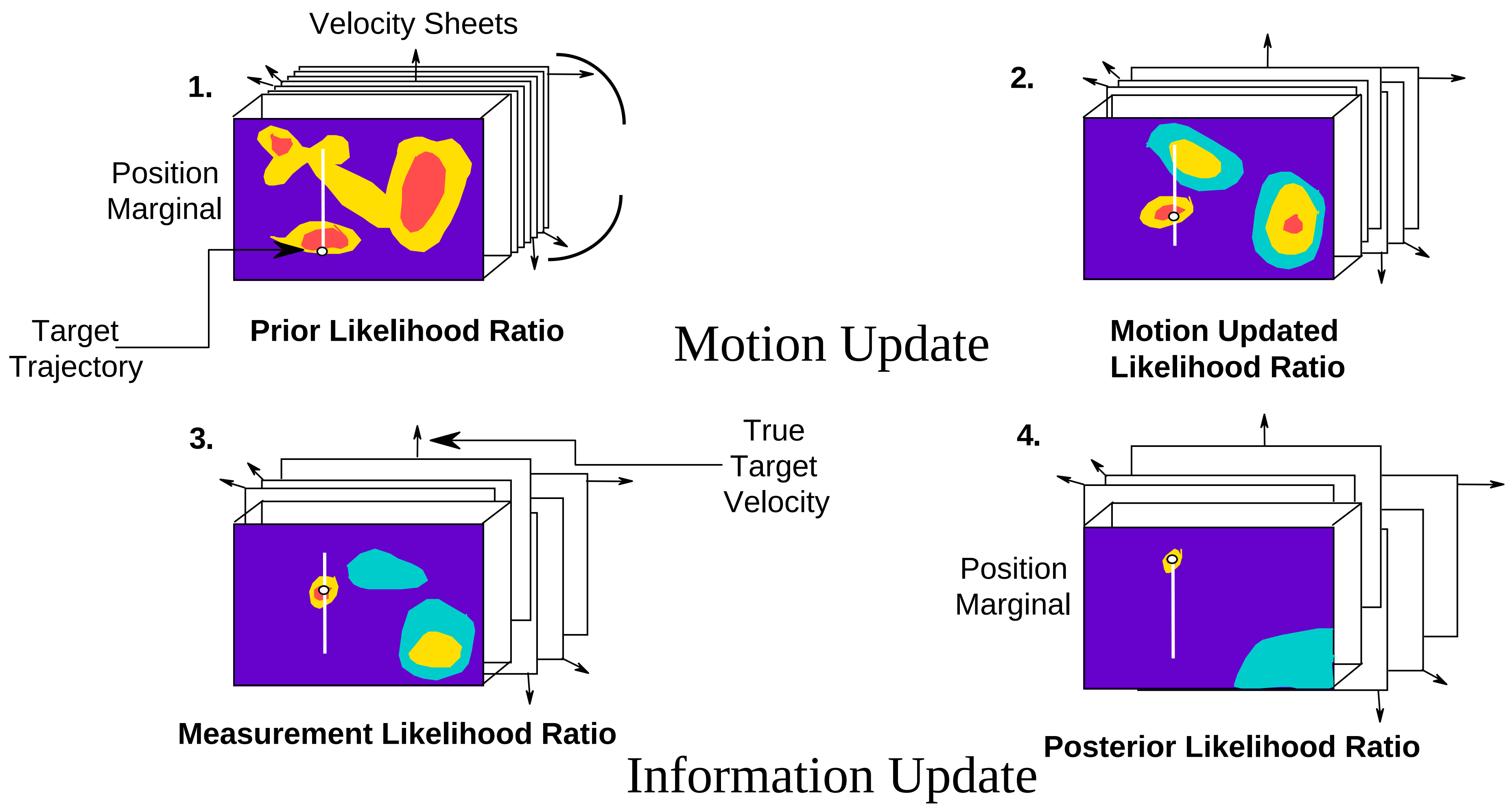
(Motion Update) $\Lambda^{-}(t_k, s) = q_k(s \mid \phi) + \int_S q(s \mid s_{k-1}) \Lambda(t_{k-1}, s_{k-1})\, ds_{k-1}$

(Information Update) $\mathcal{L}(y_k \mid s_k) = \dfrac{L_k(y_k \mid s_k)}{L_k(y_k \mid \phi)}$

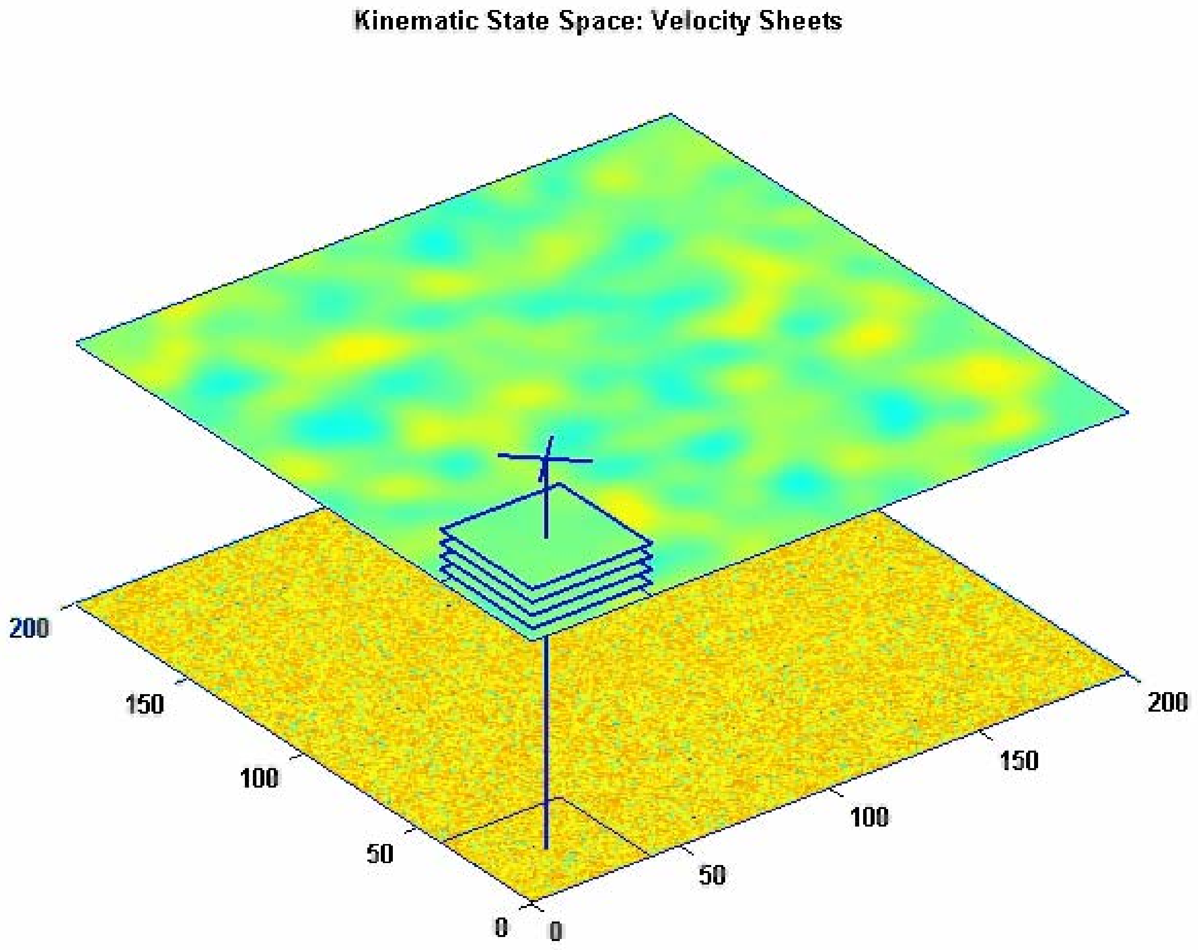
$$\Lambda_k(t_k \mid s_k) = \mathcal{L}(y_k \mid s_k) \Lambda^{-}(t_k, s)$$

(Logarithm Form) $\ln \Lambda_k(t_k \mid s_k) = \ln \mathcal{L}(y_k \mid s_k) + \ln \Lambda^{-}(t_k, s)$

LRT Implementation Schematic



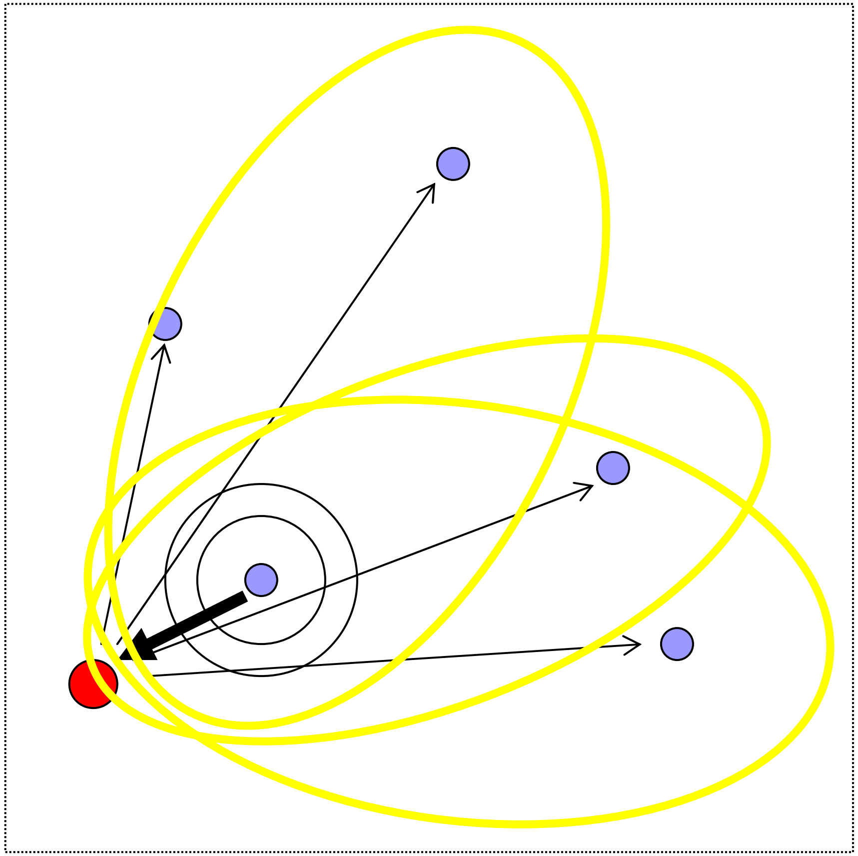
Velocity Sheet Example



Goals and Approach

- Goals
  - Show that detailed performance prediction aides likelihood ratio tracking
  - Demonstrate robustness in presence of large environmental uncertainty
- Approach
  - Add detailed detection model to LRT
  - Add environmental uncertainty to LRT state space

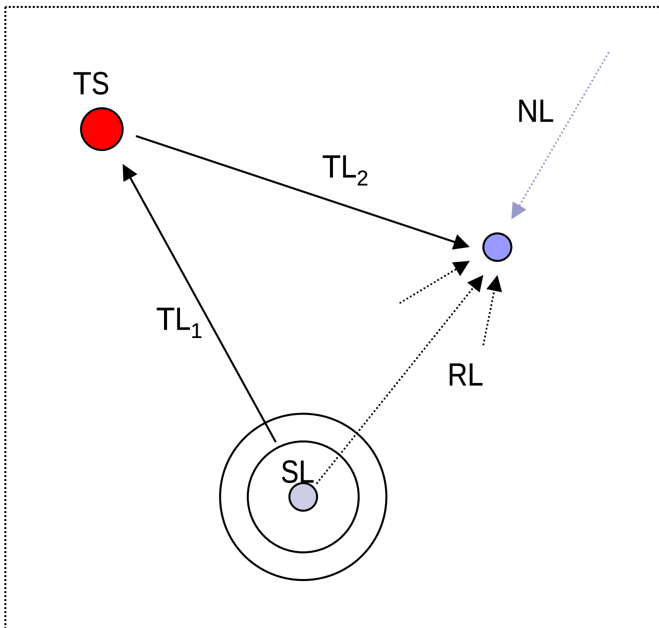
Multi-static Active Systems



- hydrophones dispersed
- target reflects blast wavefront
- reflection detected by hydrophone receivers (human or DSP algorithms)
- time of detection forms an ellipse of possible locations
- false alarms, clutter obscure target detections

Measurement: series of echo times $\mathbf{y} = (y_1, y_2, \ldots, y_n)$

Modeling Signal Excess



Signal Excess Model (Mean Level)

$$\overline{SE} = SL - TL_1 - TL_2 + TS - (RL + NL) - DT$$

Signal Excess Observations

$$\underbrace{SE}_{\text{SE Observation}} = \overline{SE} - \overbrace{d}^{\text{Model Mismatch “Uncertainty”}} + \underbrace{x \text{ where } x \sim N\left(0, \sigma_{SE}^{2}\right)}_{\text{Ping-to-Ping Fluctuations “Variability”}}$$

Detection Model

$$\text{Detection when:} \quad SE = \overline{SE} - d + x > 0$$

$$\therefore \quad P_d(\overline{SE} - d) = \int_0^{\infty} N(x, \overline{SE} - d, \sigma_{SE}^2)\, dx$$

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Variability and Uncertainty

Ocean Processes

Long* Time Scale

- uncertain SSP
- uncertain bottom
- other unknowns

Short Time Scale

- internal waves
- turbulence
- other stochastic

Signal Excess Model

$$\overline{SE} = SL - TL_1 - TL_2 + TS - (RL + NL) - DT$$

Signal Excess Uncertainty and Variability

Model Mismatch
“Uncertainty”

$$SE = \overline{SE} - \overbrace{d} + \underbrace{x \text{ where } x : N\left(0, s_{SE}^{2}\right)}$$

Ping-to-Ping Fluctuations**
“Variability”

* compared to operation timescale, O(1 hour)

** Gaussian approximation shown here

Using SE in LRT

IASW Approach

$$\mathcal{L}(\mathbf{y}|s) = P_d(s)\sum_{i=1}^{n}\frac{1}{l}\left(\frac{f(y_i|s)}{w(y_i)}\right) + (1 - P_d(s))$$

$$P_d(s) = P_d^{\mathrm{MAX}}\exp\left\{-\frac{(\varphi_0^k - \varphi(s))^2}{2\sigma_\varphi^2}\right\} \qquad \text{(IASW)}$$

Statespace Dimensions
Position
Velocity

Environmental Performance Prediction Approach

$$\mathcal{L}(\mathbf{y}|s,E) = P_d(s,E)\sum_{i=1}^{n_k}\frac{1}{l}\left(\frac{f(y_i|s,E)}{w(y_i)}\right) + (1 - P_d(s,E))$$

"Uncertainty"
State Space Dimension

(long time scales)
adds robustness

$$P_d(s,E) = \int_0^\infty \underbrace{N(x, \overline{SE}(s,E), \sigma_{SE}^2)\,dx}_{\text{"Variability" PDF}}$$

(short time scales)

Statespace Dimensions
Position
Velocity
Environmental

Environmental Dimension

Environmental Performance Prediction Approach

$$\Lambda\left(\mathbf{y}\,\middle|\,\underbrace{s,E}\right)=P_d(s,E)\sum_{i=1}^{n_k}\frac{1}{\lambda}\left(\frac{f\left(y_i\,|\,s,E\right)}{w\left(y_i\right)}\right)+\left(1-P_d(s,E)\right)$$

"Uncertainty"
State Space Dimension

(long time scales)
adds robustness

$$P_d(s,E)=\int_0^{\infty}\underbrace{N(x,\overline{SE}(s,E),\sigma_{SE}^2)}_{\text{"Variability" PDF}}\,dx$$

(short time scales)

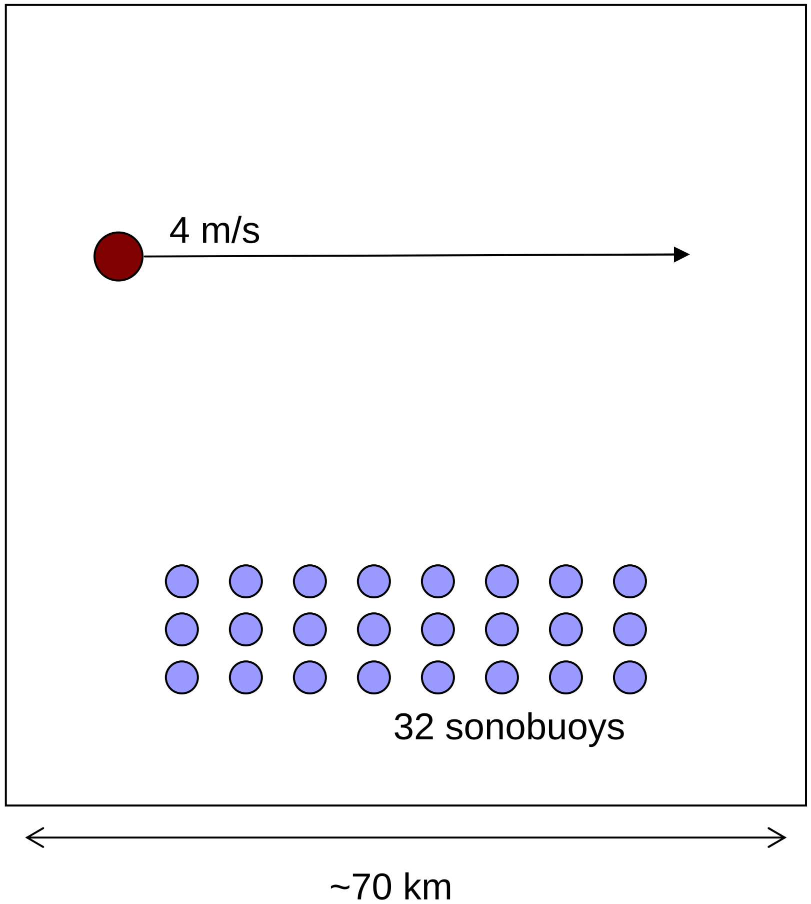
Statespace Dimensions
Position
Velocity
Environment

"Delta" Discretization of Environmental Dimension

$$\hat{E}_i\equiv\{\overline{RL},\overline{TL},d_i\}\qquad \overline{RL}=\frac{1}{N}\sum_{i=1}^{N}RL^i\qquad P_d(s,d)=\int_0^{\infty}N(x,\overline{SE}(s)-d,\sigma_{SE}^2)\,dx$$

$$\overline{TL}=\frac{1}{N}\sum_{i=1}^{N}TL^i$$

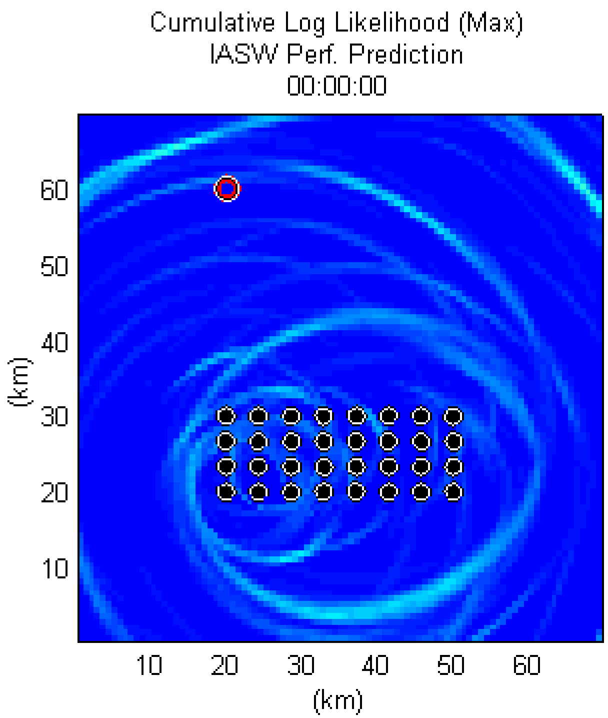
Example: Improvement due to good detection modeling

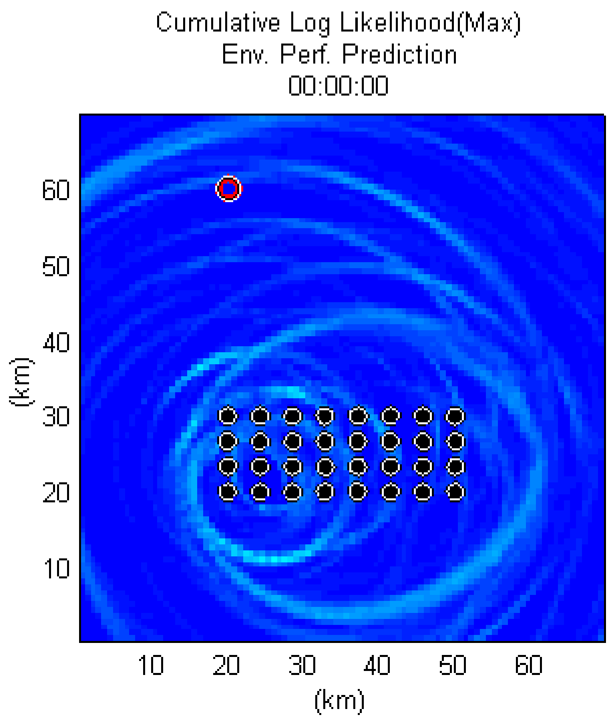


- **Simulation Parameters**
  - **RL / TL** (Reverb / Loss)
    - *in situ* SSP used
    - 750 Hz / 500 Hz band
    - Fulford Bottom Loss
  - **TS:** BASIS Bistatic Diesel Model
  - **Variability:** 8 dB (Gaussian)
  - **Exercise Parameters**
    - 90 sec dwell time
    - avg of 20 false alarms / ping / buoy
    - blast order randomized
- **Tracker Parameters**
  - **RL / TL**
    - MODAS SSP used
    - 750 Hz / 500 Hz band
    - Fulford Bottom Loss
  - **TS:** BASIS Bistatic Diesel Model
  - **Uncertainty:** -5 dB to 5 dB
  - **Variability:** 8 dB (Gaussian)

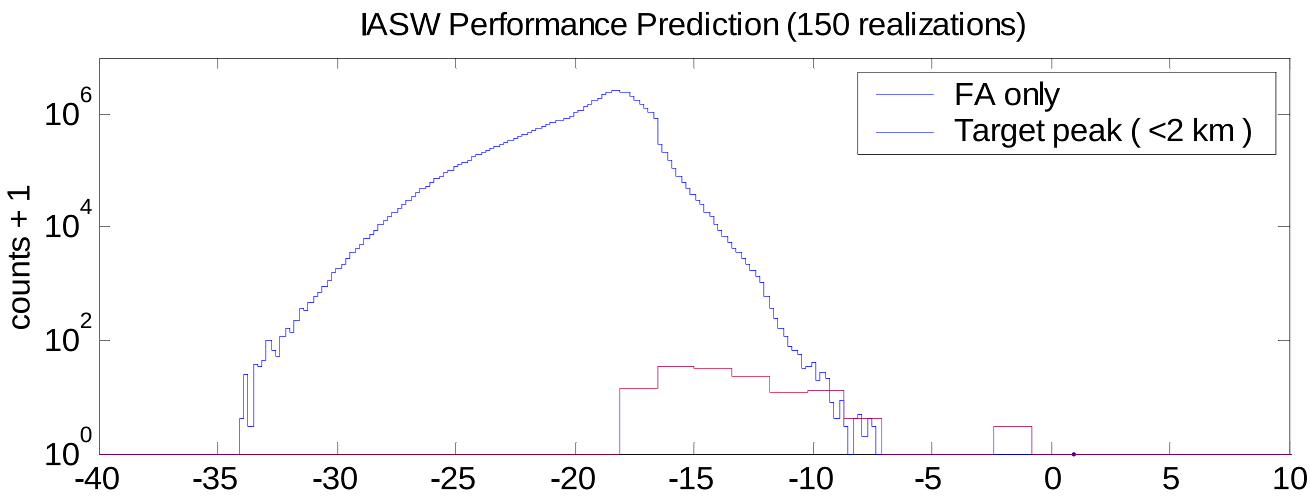
Results: Cumulative Likelihood Example

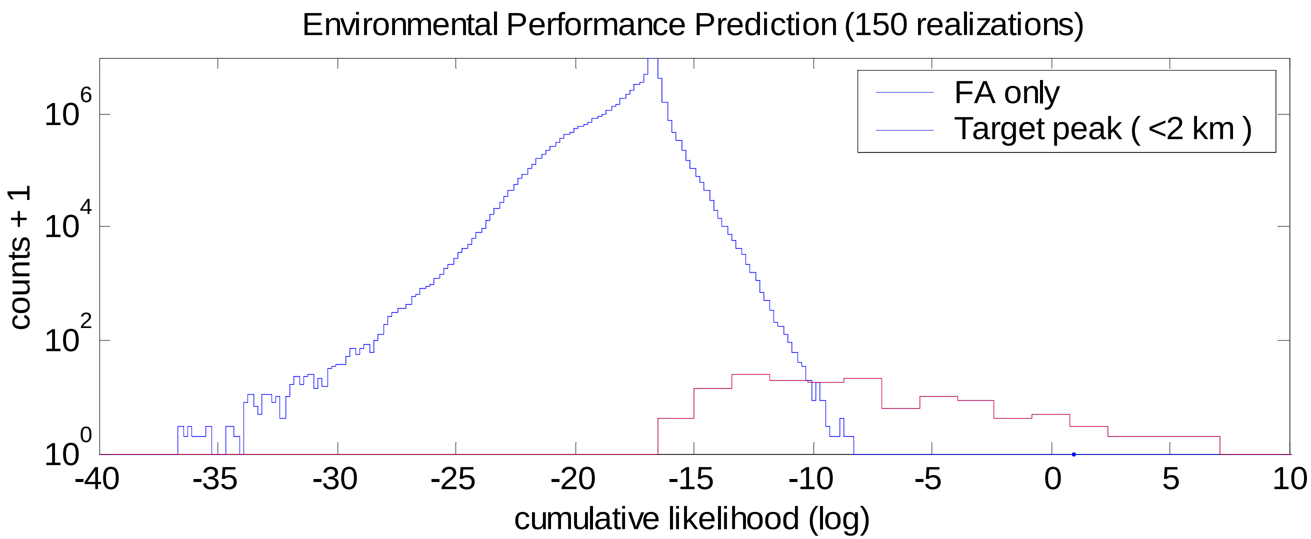
Video



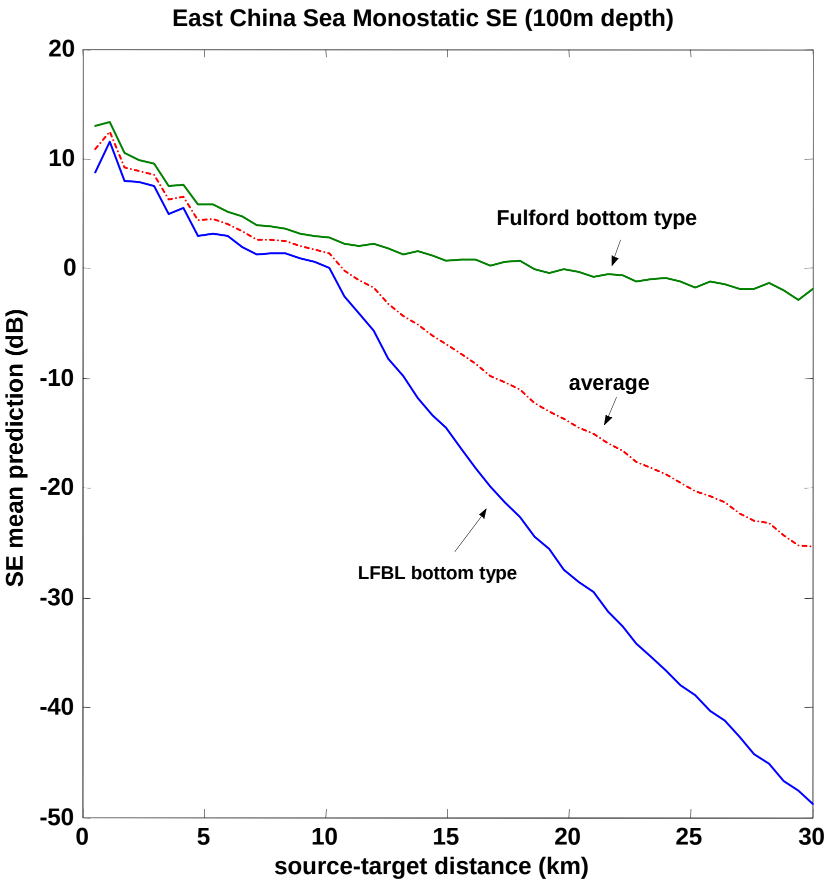


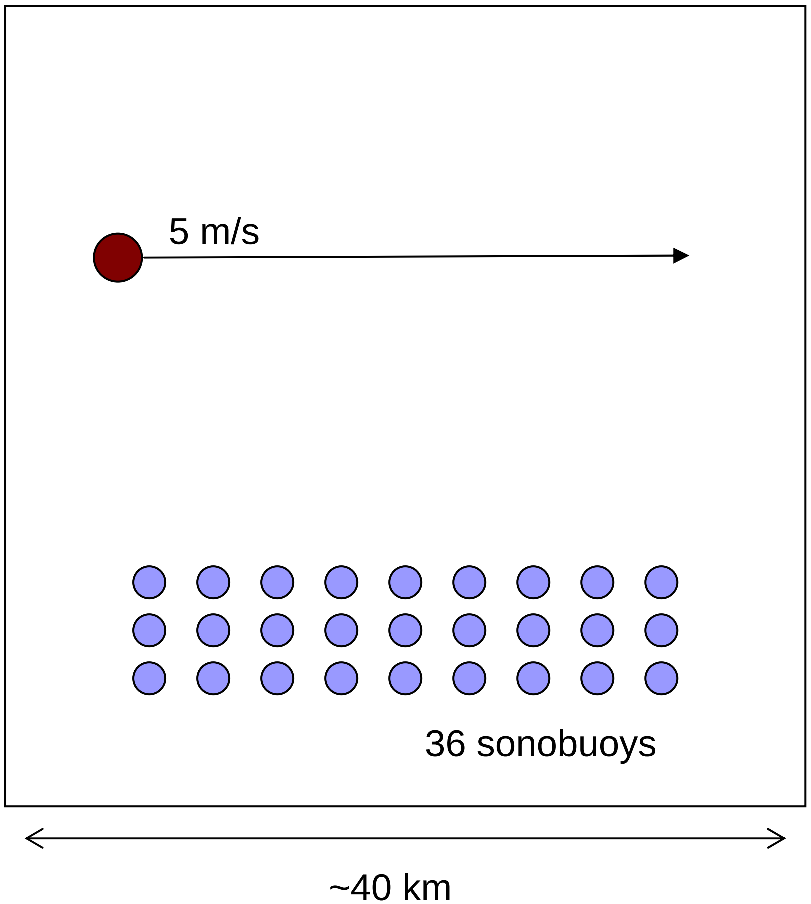
Results: Cumulative Likelihood Histograms



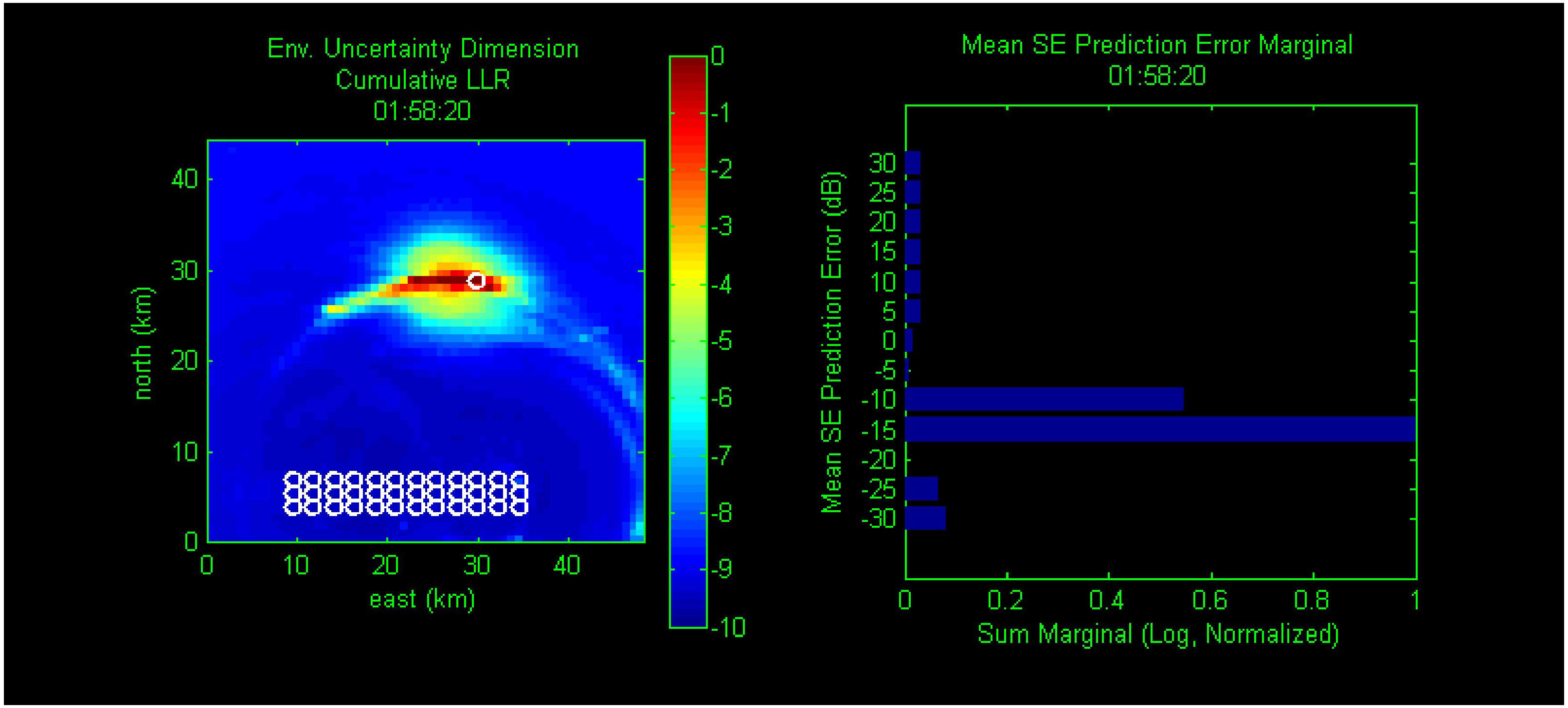


Example: Robustness to high Uncertainty

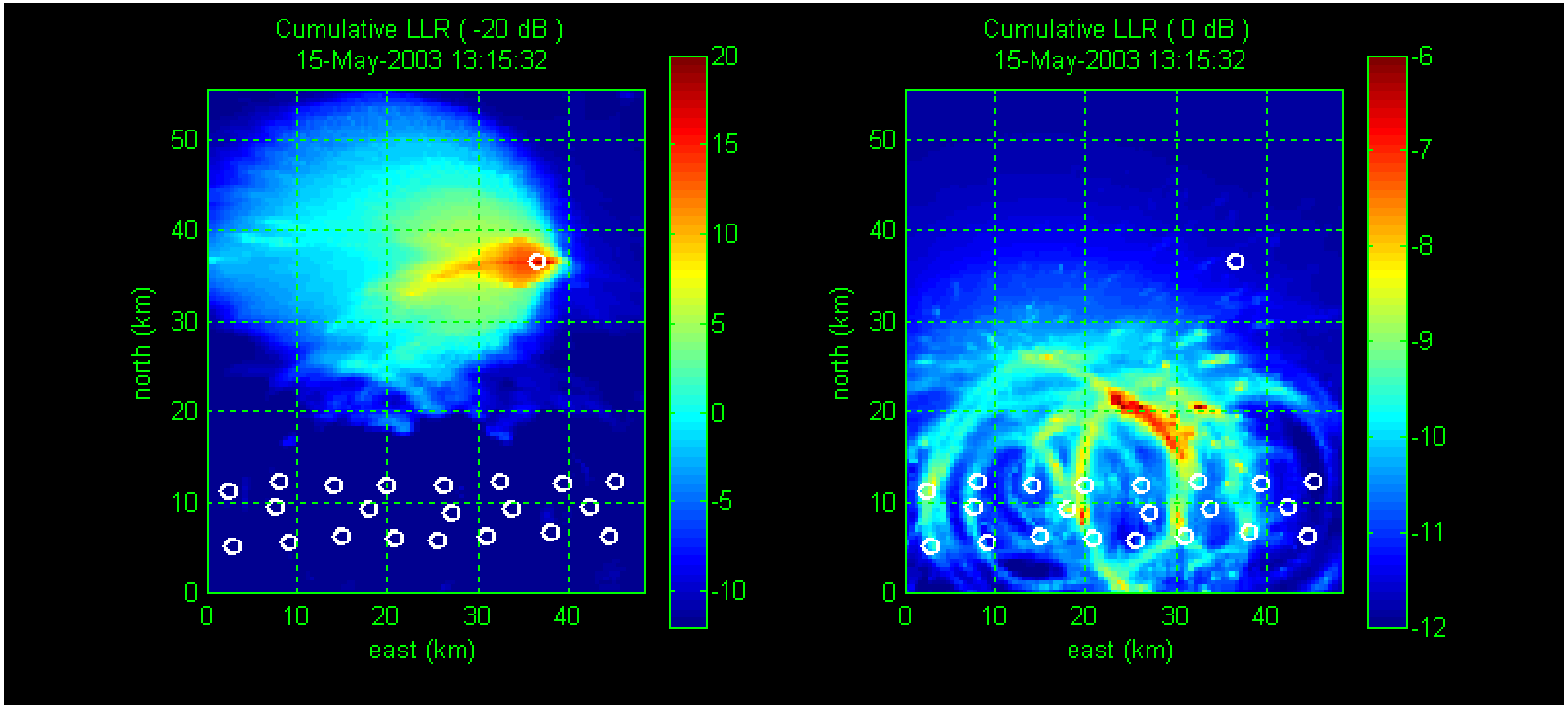




Results (High Environmental Uncertainty)



Results (High Environmental Uncertainty)



Conclusions

- Use of performance prediction improves tracker performance compared to IASW measurement likelihood ratio function.

- Accounting for environmental uncertainty allows LRT to track in cases of large performance prediction uncertainty.

Publications

- "Effect of Environmental Prediction Uncertainty on Target Detection and Tracking" by L. D. Stone and Bryan R. Osborn, *Proceedings of SPIE conference on Defense and Security*, April 2004
- This work will appear in the JUA issue on Sensor Performance Prediction Analysis