Exploring the Underwater Environment:

Applications of beamforming and Bayesian inference to sonar array processing.

Jason Ralph

Signal Processing Group,

School of EEECS, UoL

Exploring the Underwater Environment:

Applications of beamforming and Bayesian inference to sonar array processing.

JR, Simon Maskell, Angel Garcia-Fernandez, Murat Uney, Phil Clemson, Alexey Narykov, Michael Wright, Chris Taylor

and the National Oceanography Centre (NOC)

Sourav Sahoo, Gaye Bayracki, Angus Best, Matthew Palmer

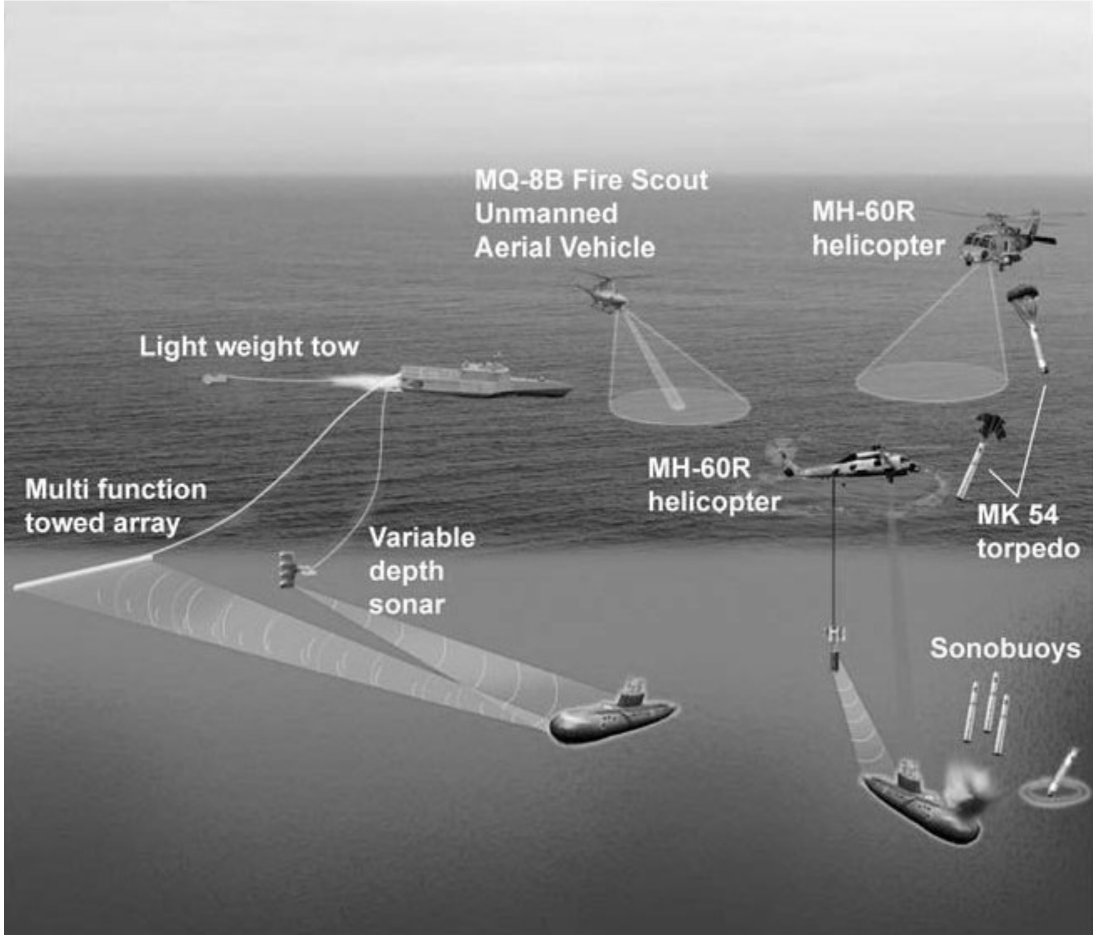
Outline

- Sonar Systems
  - Towed Arrays, Flank Arrays, Bow Mount, Dipping Sonars, Sonobuoys, Torpedoes,…
- Signal Propagation and Noise
  - Ray Tracing & Wave Propagation
  - Reverberation & Biologicals
- Direction-of-Arrival
  - Conventional beamformer
  - Adaptive/Capon beamformer
  - Bayesian/MCMC beamformer
- Target Tracking in Clutter
  - Sensor Noise Characterisation
  - Stone Soup
- Summary and Future Work

UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Sonar

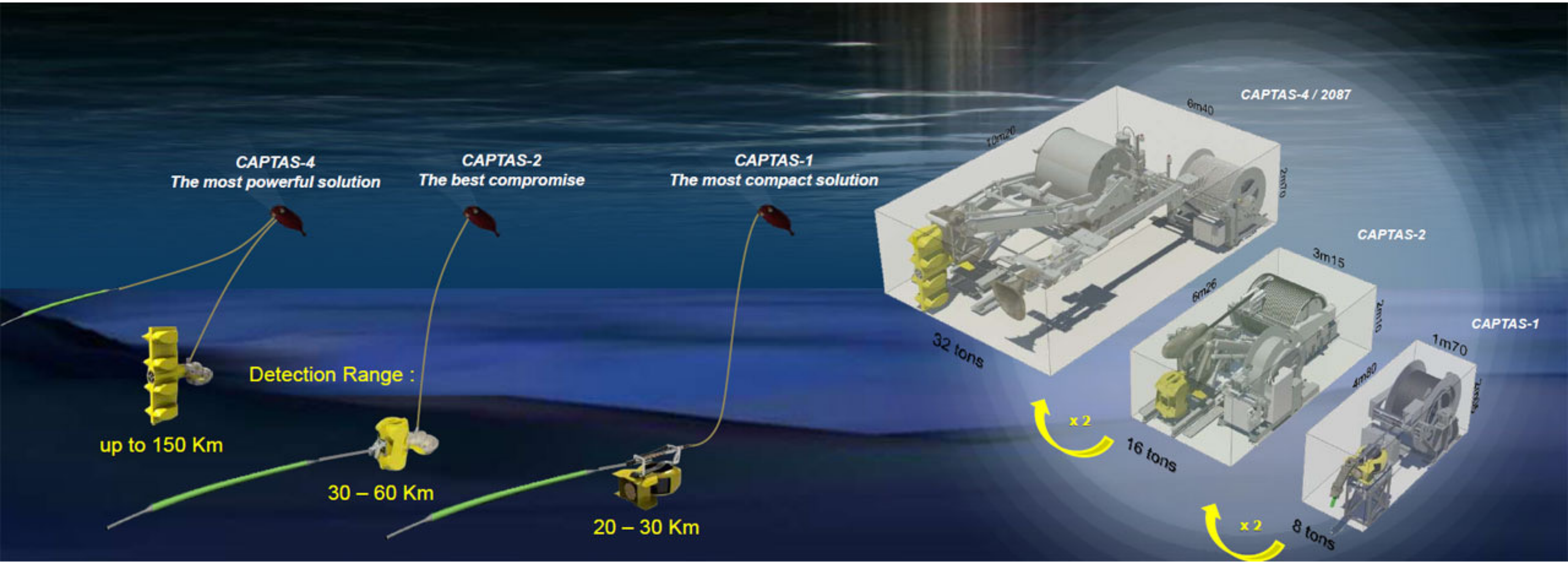


UNIVERSITY OF LIVERPOOL

National Oceanography Centre

https://news.usni.org/2015/08/04/navsea-cutting-weight-on-littoral-combat-ship-asw-mission-package-not-a-new-problem

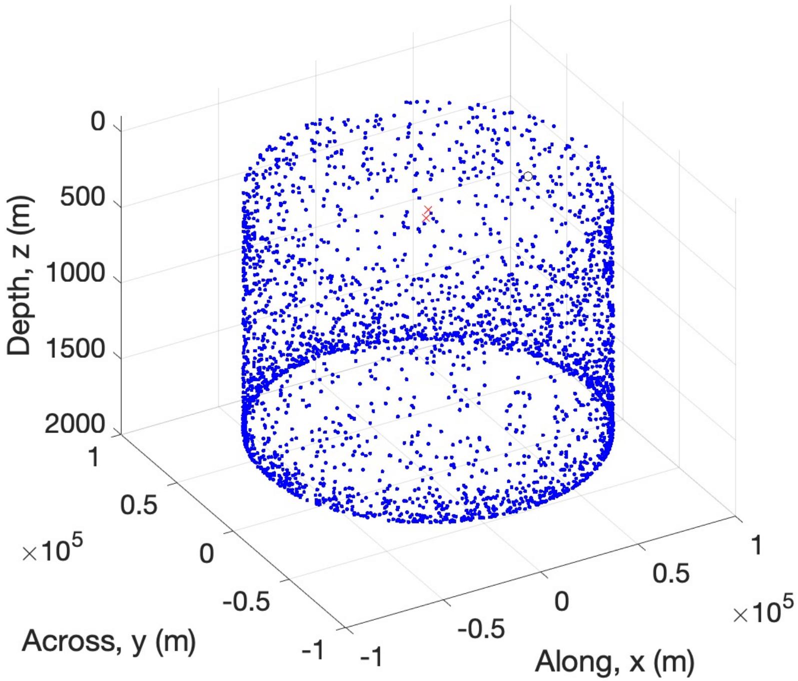
Towed Arrays – E.g. Thales CAPTAS Family

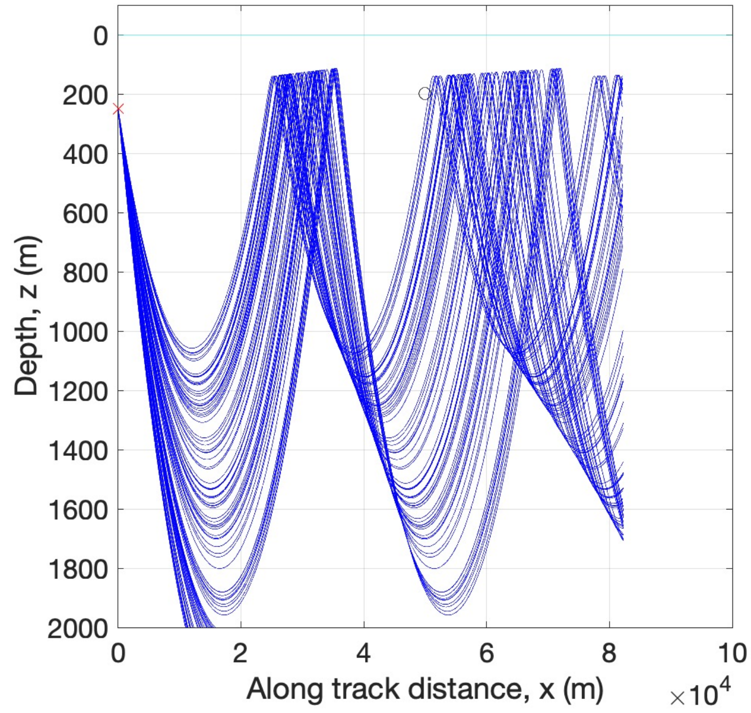


University of Liverpool | National Oceanography Centre

https://www.defesaaereanaval.com.br/artigos/thales-underwater-systems-sas-brest?PageSpeed=noscript

Towed Array – Active Sonar Propagation

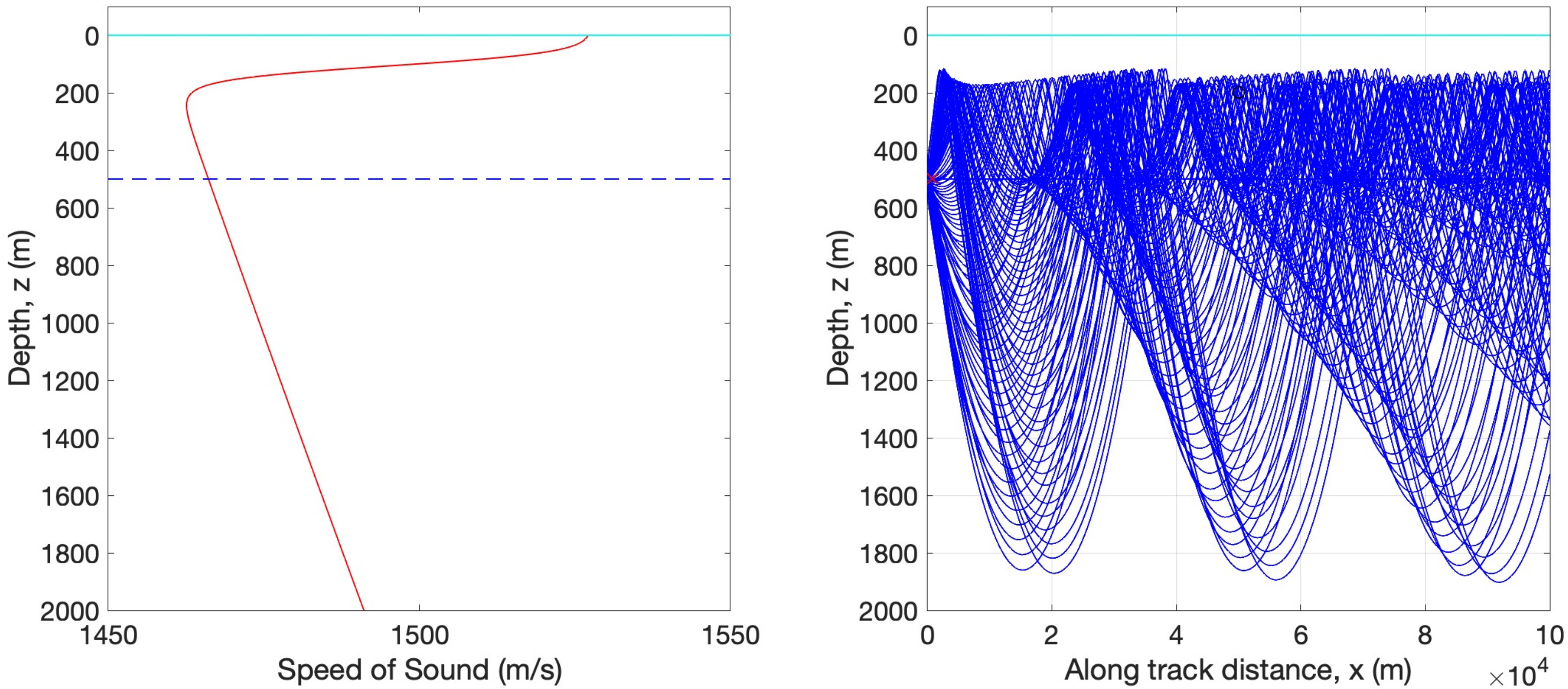




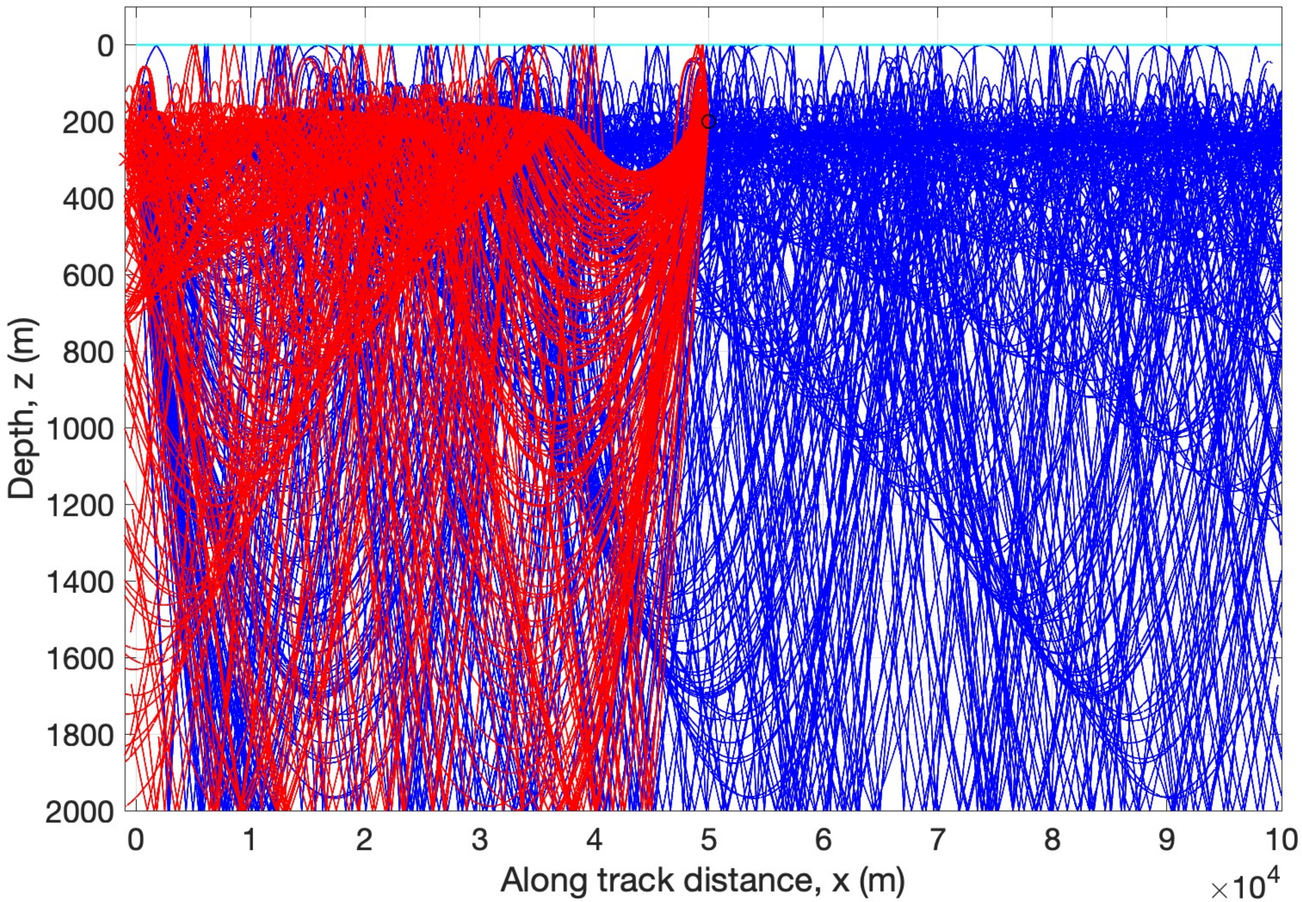
UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Towed Array – Transmitter Placement



Reflected signals…

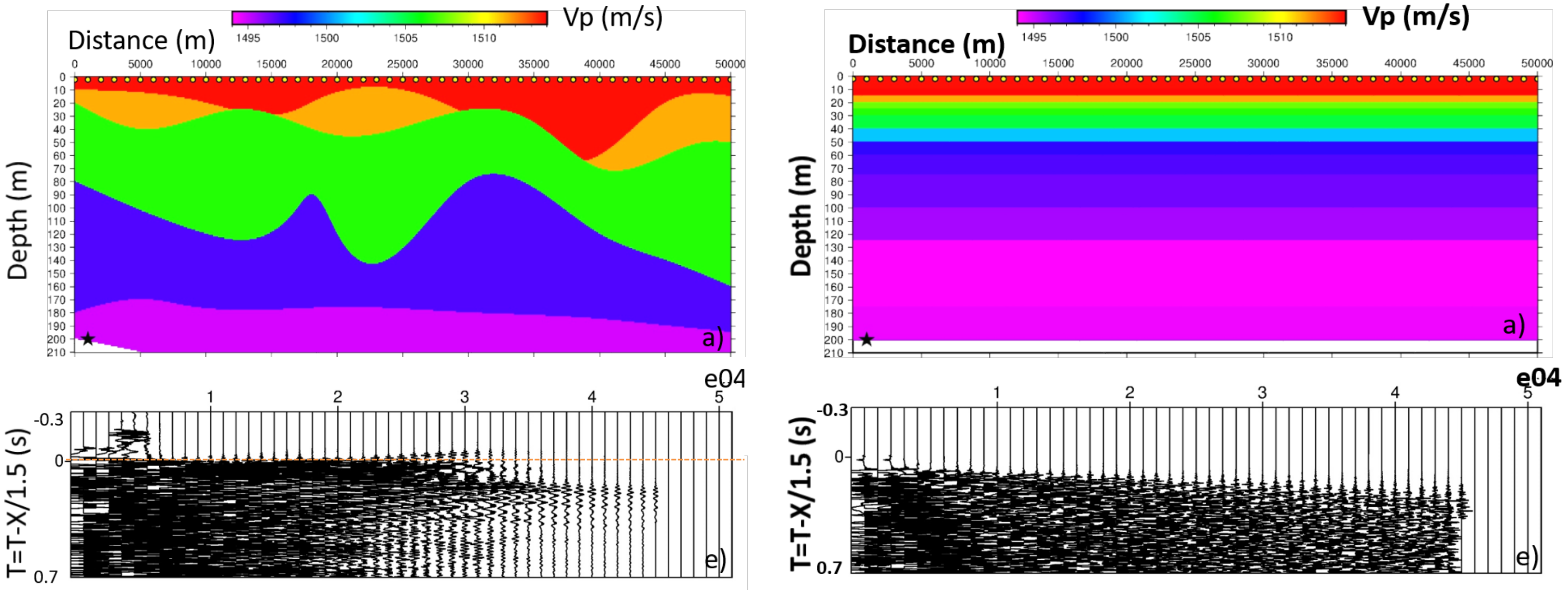


UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Simulation and Modelling

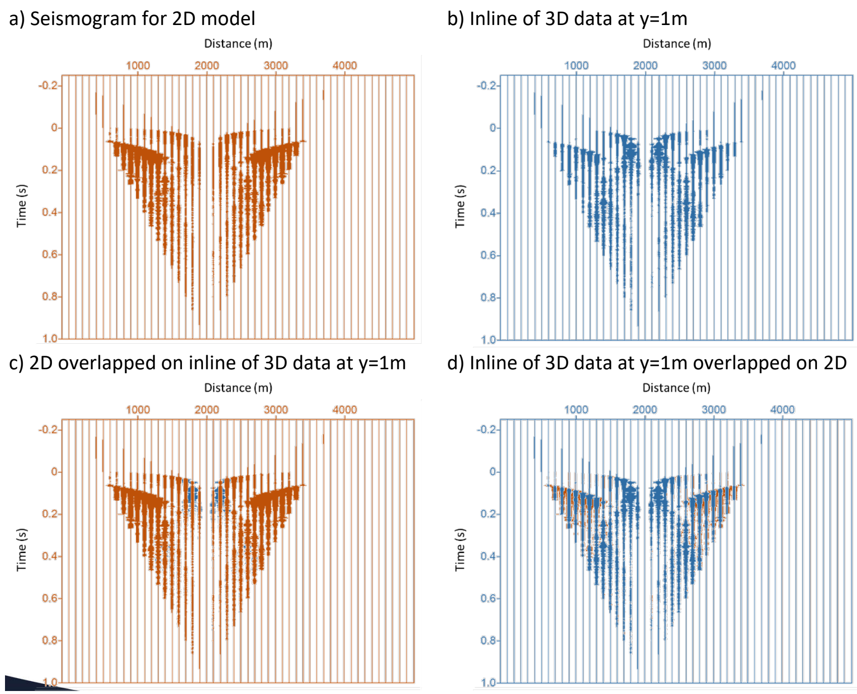
- Heterogenous versus Layered Ocean Models



  - Investigating the effects of realistic ocean structures on sonar propagation models
  - Gradient versus layered models
  - 3D versus 2D models
  - Inclusion of real ocean data

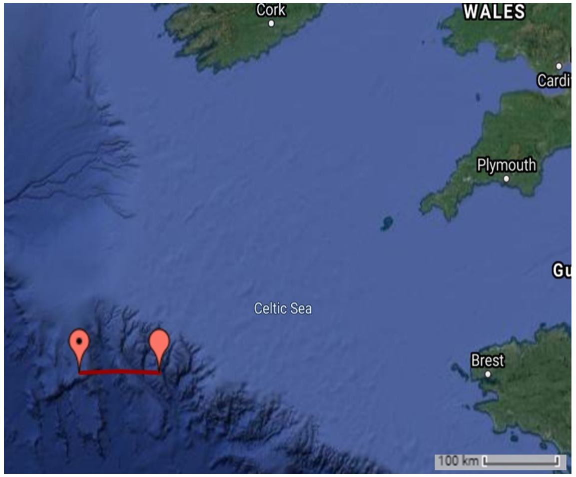
Simulation and Modelling

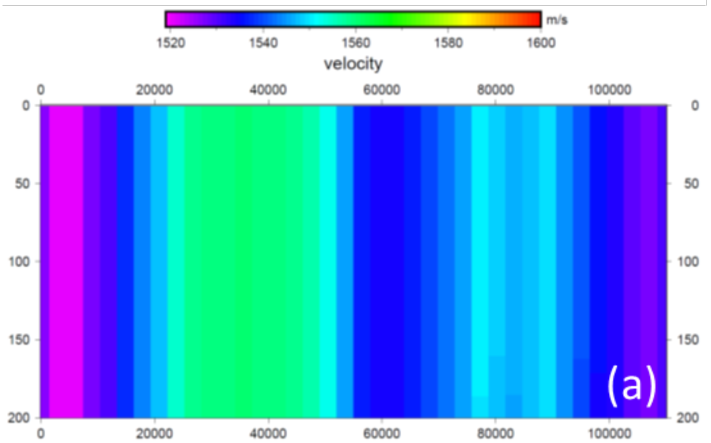
- Comparison of 2D and 3D Ocean Models



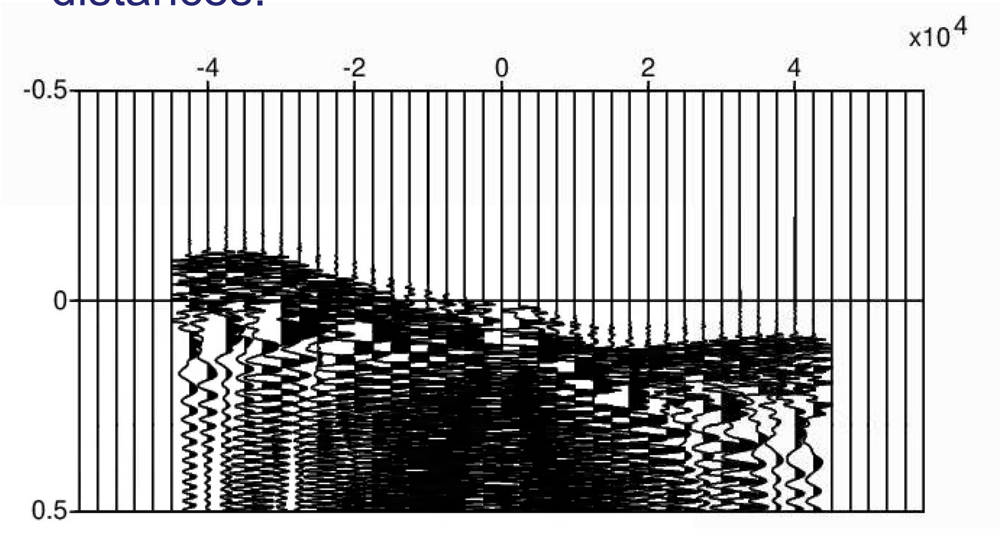
  - Same configuration, No travel time differences
  - 2D model shows higher amplitudes for near offset traces, but lower for the far offsets.
  - If a source is to be detected from signal amplitude, then 2D modelling may give over-optimistic results compared to 3D case.

Water column data



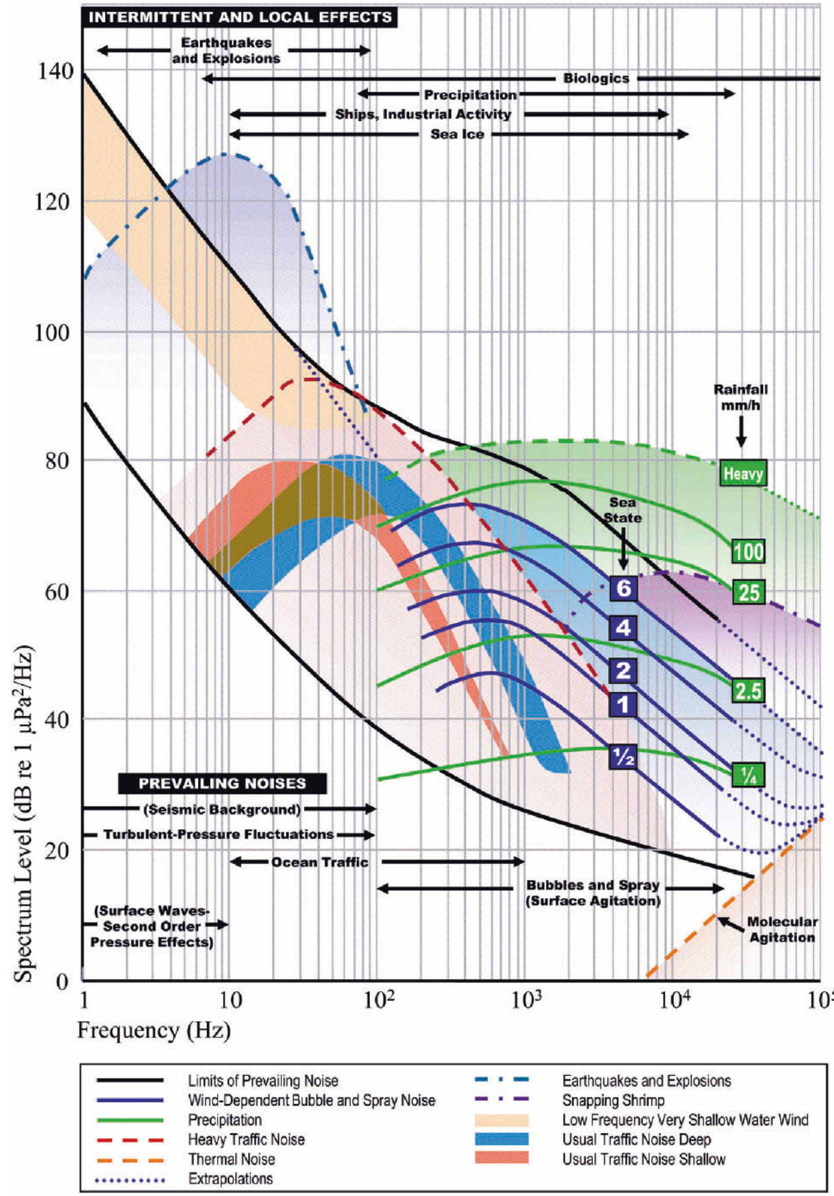


- Velocity varies horizontally – shelf areas
- Data from top 200m
- No seafloor in modelling
- Signal data below are presented 'flattened' in the y-axis to compare signals at different distances.



Sources of Noise

- Sea Noise
  - Waves
  - Bubbles and Spray
  - Tides
- Weather
  - Rain and Wind/Sea State
- Shipping
  - Lower frequency engine and propeller noise
  - Other Sonar
- Biological Sources
  - Whales and other Cetaceans
  - Snapping Shrimps



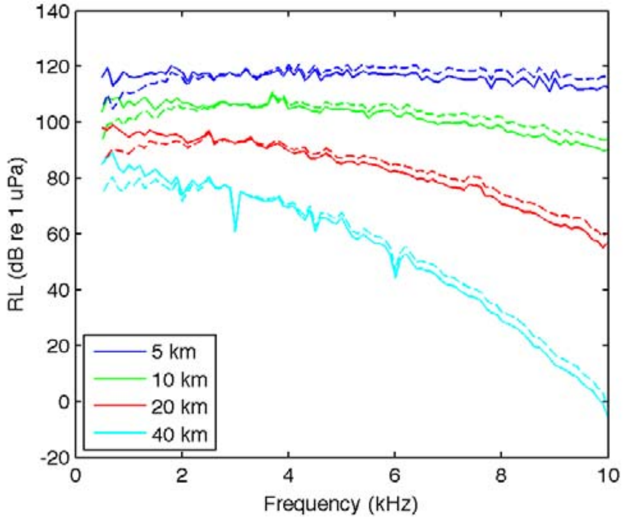
Typical ambient noise spectra (Michael A. Ainslie "Principles of Sonar Performance Modeling" (Springer, 2010), originally in Wenz, 1962, American Institute of Physics)

UNIVERSITY OF LIVERPOOL

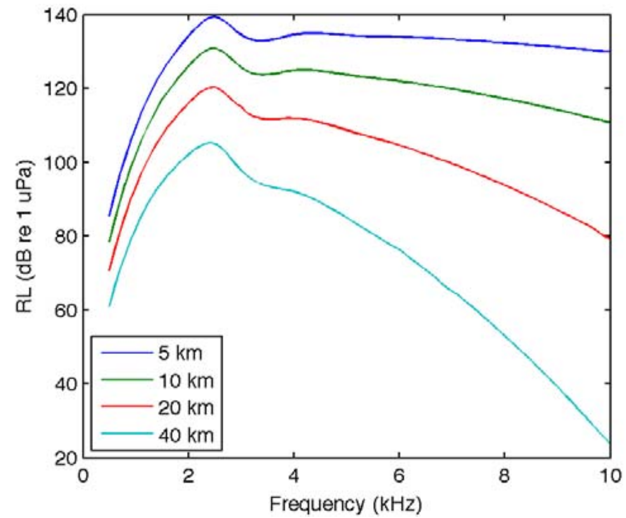
National Oceanography Centre

Reverberation

- Reverberation is noise arising from scattering of the transmitted sonar by environmental factors not associated with the target of interest.
  - Underwater boundaries (refraction and reflection of sound waves)
  - Scatterers – obstacles, ocean floor clutter, debris, bubbles, and fish
- Reverberation ultimately limits the power that can be used by active sonar.



Reverberation level (RL) for frequency-independent (solid lines) and data-derived, frequency- dependent (dashed lines) scattering strengths at one-way travel distances of 5, 10, 20 and 40 kilometres.



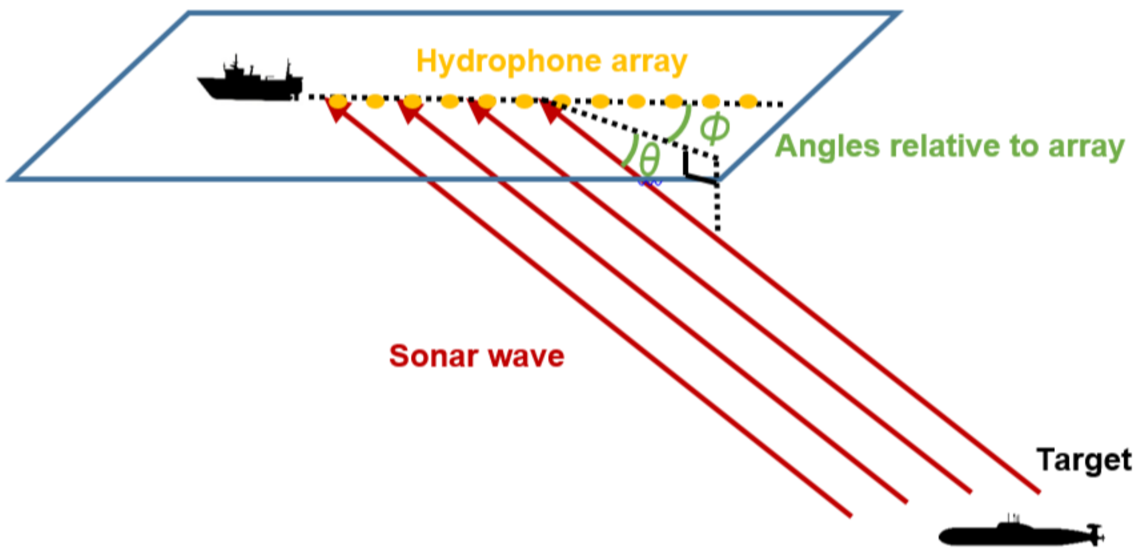
Reverberation level (RL) due to volume scattering from biologics, in this case anchovies

Colin W. Jemmott, and William K. Stevens "The impact of reverberation on active sonar optimum frequency ", Proc. Mtgs. Acoust. 12, 070001 (2011)

BEAMFORMING

Beamforming

- Beamforming is a technique used to determine the direction of arrival (DoA) of a wave (e.g. radio, sonar).
- The beamformer spectrum shows the amount of energy arriving from each angular direction, with the target DoA showing as a peak.

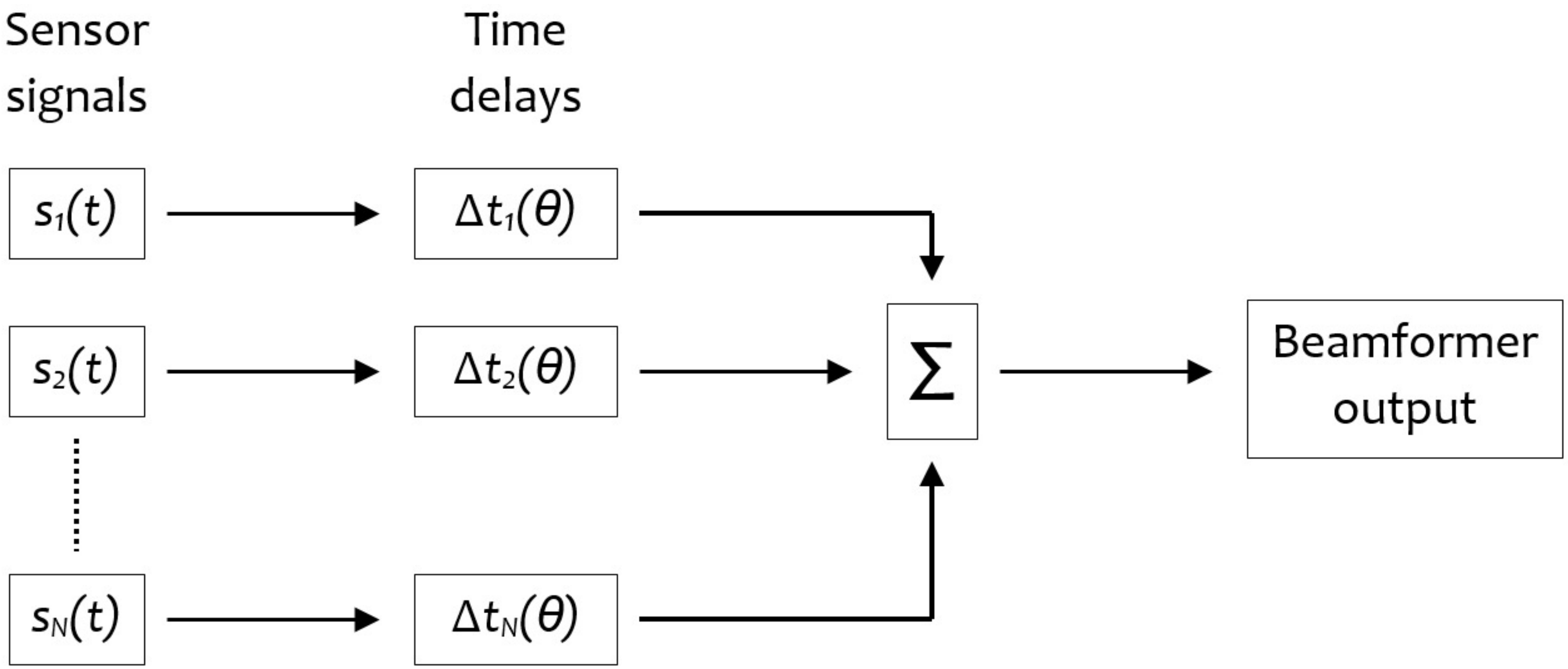


UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Conventional Beamformer

- Conventional beamformers are a specific class of beamforming algorithms. One of the most common is the delay-and-sum (DAS) beamformer, which combines the signals si of the receiver array using fixed time delays corresponding to each angular direction.



Conventional Beamformer

- For the angle θ, the amplitude of the beamformer is defined as

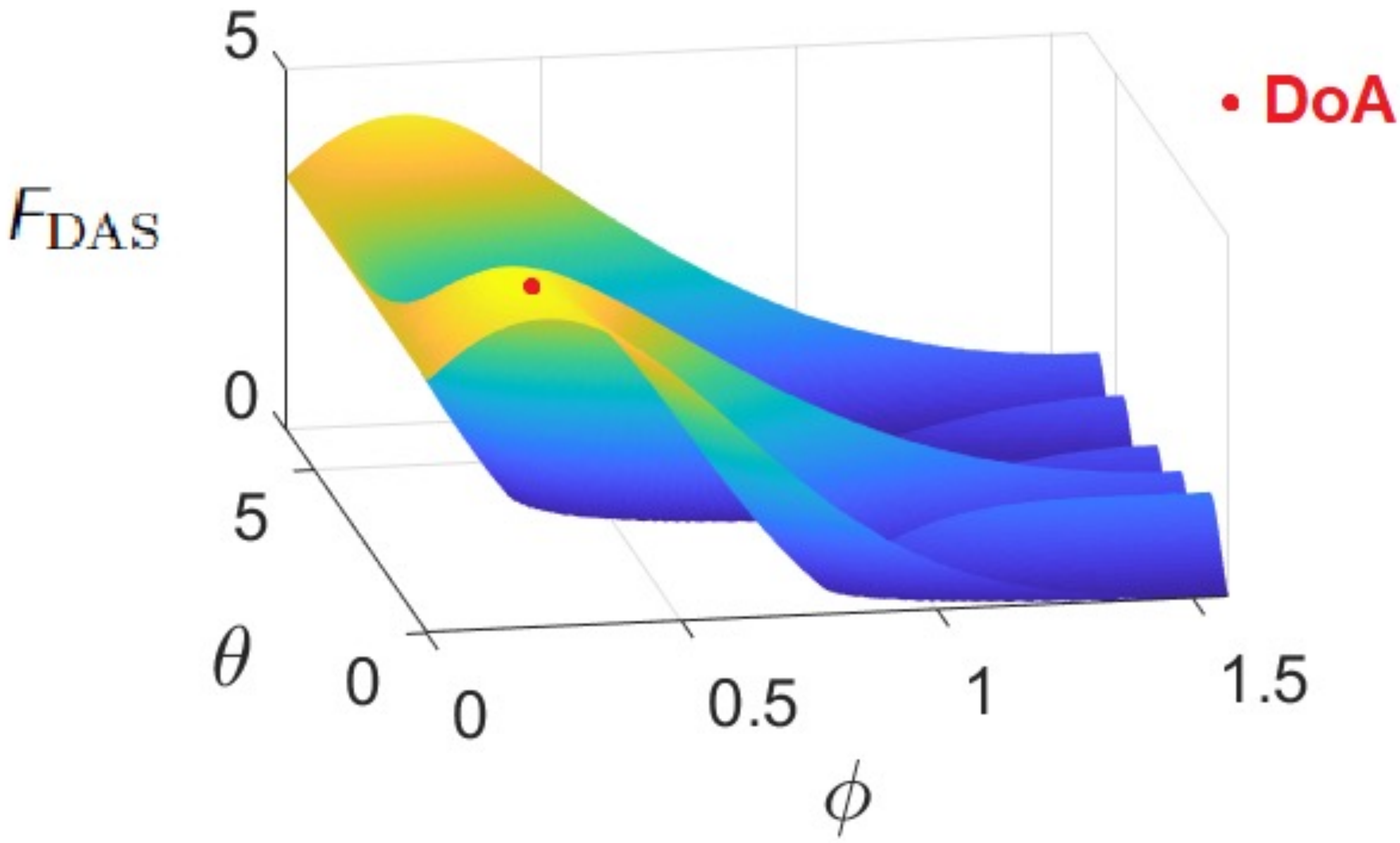
$$F_{\mathrm{DAS}}(\theta) = \frac{1}{N}\sum_{i}^{N}\left[\frac{1}{T - \Delta t_i(\theta)}\int_0^{T-\Delta t_i(\theta)} s_i(t)s_i(t + \Delta t_i(\theta))dt\right] \quad (1)$$

$$\Delta t_i(\theta) = \frac{\mathbf{a}_\theta \mathbf{z}_i^T}{c} \quad (2)$$

where
M = the number of array sensors
T = the length of the measured signals in time
c = the wave speed
$\mathbf{a}_\theta$ = the Cartesian unit vector corresponding to θ
$\mathbf{z}_i$ = the Cartesian position vector of the sensor

H. L. Van Trees, Optimum Array Processing: Part IV of Detection, Estimation, and Modulation Theory, Wiley, 2002

Conventional Beamformer



Adaptive Beamformers

- Adaptive beamformers are another class of beamforming algorithms. They are distinguished by the fact that the filter design contains variable delays and amplitude weights.

- The Capon beamformer minimizes the influence of signals from angular directions close to θ by using weights defined as

$$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{R} \mathbf{w} \text{ such that } \mathbf{w}^H \mathbf{v}(\theta) = 1 \tag{3}$$

$$\mathbf{v}(\theta) = \left[e^{j\omega \mathbf{a}_\theta^T \mathbf{z}_1}, e^{j\omega \mathbf{a}_\theta^T \mathbf{z}_2}, \ldots, e^{j\omega \mathbf{a}_\theta^T \mathbf{z}_N} \right] \tag{4}$$

$$R_{n,m} = \frac{1}{L-1} \sum_t (s_n(t) - \bar{s}_n)(s_m(t) - \bar{s}_m) \tag{5}$$

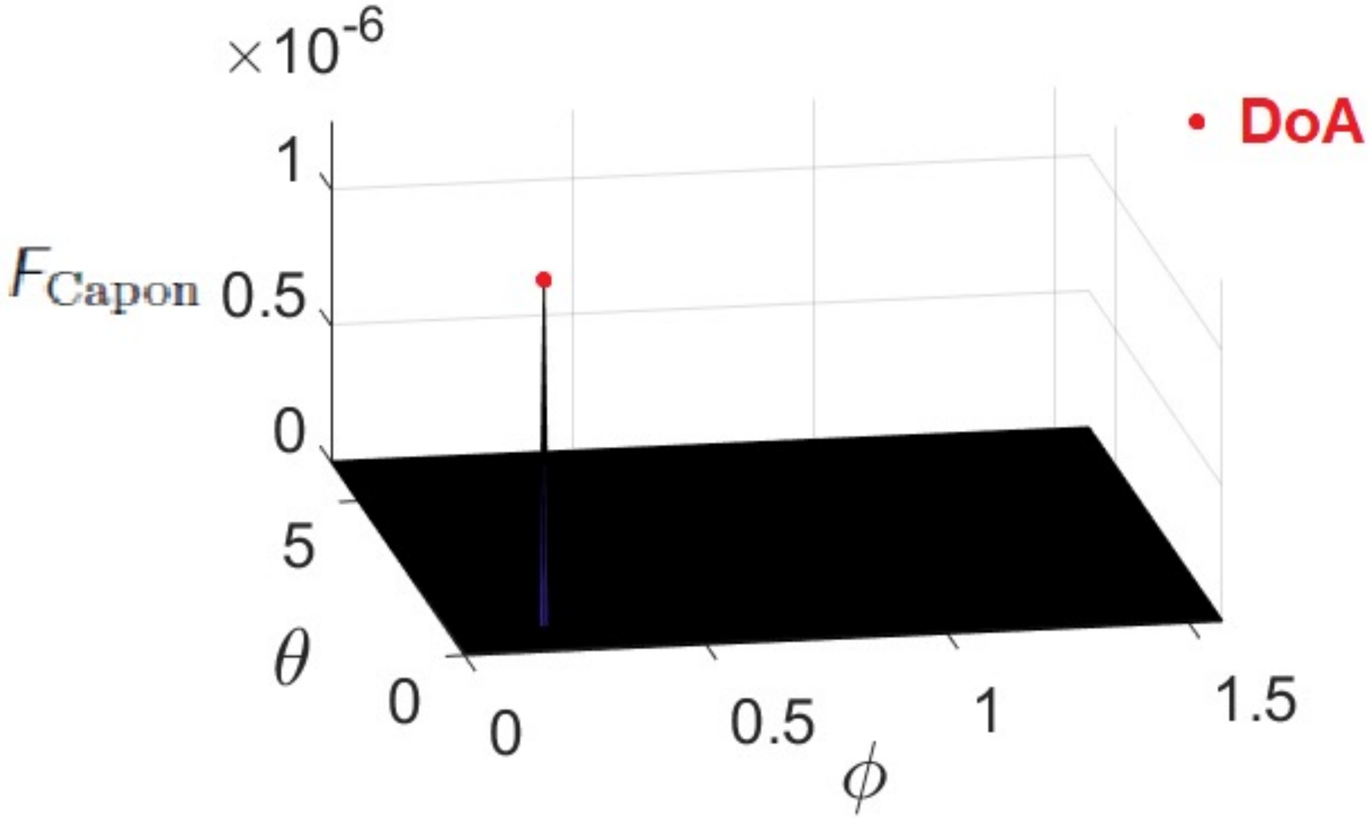
$$\Rightarrow F_{\text{Capon}}(\theta) = \frac{1}{\mathbf{v}^T \mathbf{R}^{-1} \mathbf{v}} \tag{6}$$

where L is the number of samples in the time series.

UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Capon Beamformer



J. Capon, High-Resolution Frequency-Wavenumber Spectrum Analysis, Proceedings of the IEEE, 57(8):1408–1418, 1969

Bayesian/MCMC Beamformer

- Rather than considering DoA estimation a spectral analysis problem we can instead propose a statistical model for the measured data:

$$S = G_\theta b + \varepsilon \tag{7}$$

$$G_\theta = \begin{bmatrix} \sin(\omega t + \alpha_{1,1}(\theta)) & \sin(\omega t + \alpha_{1,2}(\theta)) & \dots & \sin(\omega t + \alpha_{1,M}(\theta)) \\ \sin(\omega t + \alpha_{2,1}(\theta)) & \sin(\omega t + \alpha_{2,2}(\theta)) & \dots & \sin(\omega t + \alpha_{2,M}(\theta)) \\ \vdots & \vdots & \ddots & \vdots \\ \sin(\omega t + \alpha_{N,1}(\theta)) & \sin(\omega t + \alpha_{N,2}(\theta)) & \dots & \sin(\omega t + \alpha_{N,M}(\theta)) \end{bmatrix} \tag{8}$$

where

$$\begin{aligned} S &= [s_1(t), s_2(t), \dots, s_N(t)] \\ b &= 1 \times M \text{ vector of weights} \\ M &= \text{the number of signals (sonar targets)} \\ \alpha_{i,m}(\theta) &= \text{the phase differences between the sensors} \\ \varepsilon &= \text{additive Gaussian noise with a variance } \sigma^2 \end{aligned}$$

Bayesian/MCMC Beamformer

(7) can be rewritten as the equivalent probabilistic equation

$$p(S|\sigma^2, b, \theta) = \mathcal{N}(S; G_\theta b, \sigma^2), \tag{9}$$

which denotes the **likelihood** (goodness of fit) of the parameters σ^2, b and θ to the data.

However, we are interested in the probability $p(\theta|S)$. A solution can be found by using Bayes' rule,

$$p(\theta|S) = \frac{p(S|\theta)p(\theta)}{p(S)}, \tag{10}$$

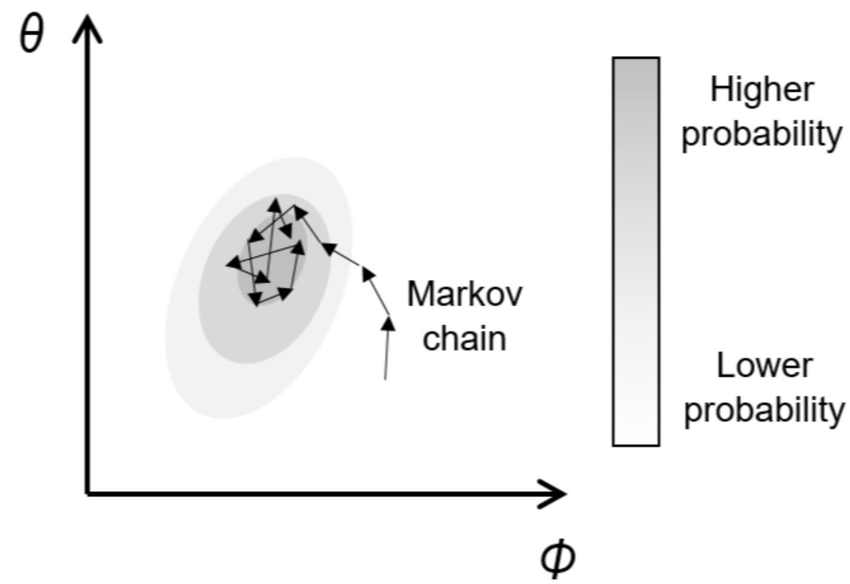
where $p(\theta|S)$ is known as the **posterior** probability and $p(\theta)$ is the **prior** probability.

Christophe Andrieu, Nando De Freitas, and Arnaud Doucet. Robust full Bayesian learning for radial basis networks. Neural Computation, 13(10):2359–2407, 2001.
Christophe Andrieu and Arnaud Doucet. Joint Bayesian model selection and estimation of noisy sinusoids via reversible jump MCMC. Signal Processing, IEEE Transactions on, 47(10):2667–2676, 1999.
Peter J. Green. Reversible jump Markov chain Monte Carlo computation and Bayesian model determination, Biometrika, 82(4):711–732, 1995.

Bayesian/MCMC Beamformer

- We can numerically sample from a posterior probability distribution using Markov chain Monte Carlo (MCMC).

  - Define $p(\theta|S)$ as the stationary target distribution of a stochastic process.
  - The Markov chain has a higher chance of accepting a randomly-proposed step in the parameter space if the $p(\theta|S)$ at that location is high.
  - Each step then represents a sample from $p(\theta|S)$.



Bayesian/MCMC Beamformer

- The number of targets M is unknown, which means it must also be estimated by the model. This can be achieved using reversible-jump MCMC.

- Propose birth and death moves to add and remove potential targets

- Ensures detailed balance is preserved ⇒ Markov chain is not biased by the direction it travels

- $p(\theta|S)$ contains many dot products between S and G_θ. If we did this for every MCMC step the algorithm would be very slow!

- Can pre-calculate prior to running the MCMC algorithm (equivalent to using phasors) e.g.

UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Bayesian/MCMC Beamformer

$$\sum_{t=0}^{L-1} s_i(t)\sin(\omega t + \alpha_{i,m})$$

$$= \begin{bmatrix} \sin(\alpha_{i,m}) & \sin(\omega + \alpha_{i,m}) & \dots & \sin(\omega(L-1) + \alpha_{i,m}) \end{bmatrix} \begin{bmatrix} s_i(0) \\ s_i(1) \\ \vdots \\ s_i(L-1) \end{bmatrix}$$

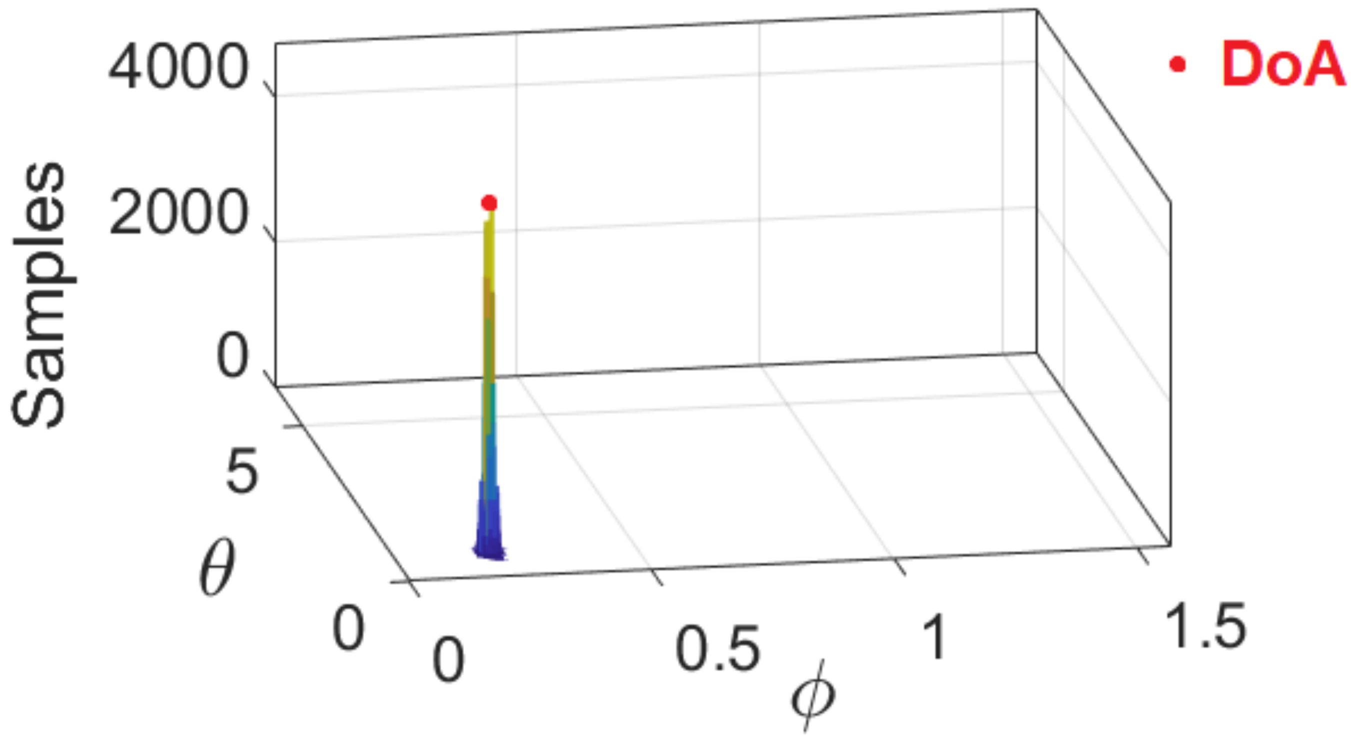
$$= \begin{bmatrix} \cos(\alpha_{i,m}) & \sin(\alpha_{i,m}) \end{bmatrix} \begin{bmatrix} \sin(0) & \sin(\omega) & \dots & \sin(\omega(L-1)) \\ \cos(0) & \cos(\omega) & \dots & \cos(\omega(L-1)) \end{bmatrix} \begin{bmatrix} s_i(0) \\ s_i(1) \\ \vdots \\ s_i(L-1) \end{bmatrix}$$

$$= \begin{bmatrix} \cos(\alpha_{i,m}) & \sin(\alpha_{i,m}) \end{bmatrix} \underbrace{\begin{bmatrix} [\sin(\omega t)]^T s_i(t) \\ [\cos(\omega t)]^T s_i(t) \end{bmatrix}}_{\text{can be computed prior to MCMC algorithm}}$$

UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Bayesian/MCMC Beamformer

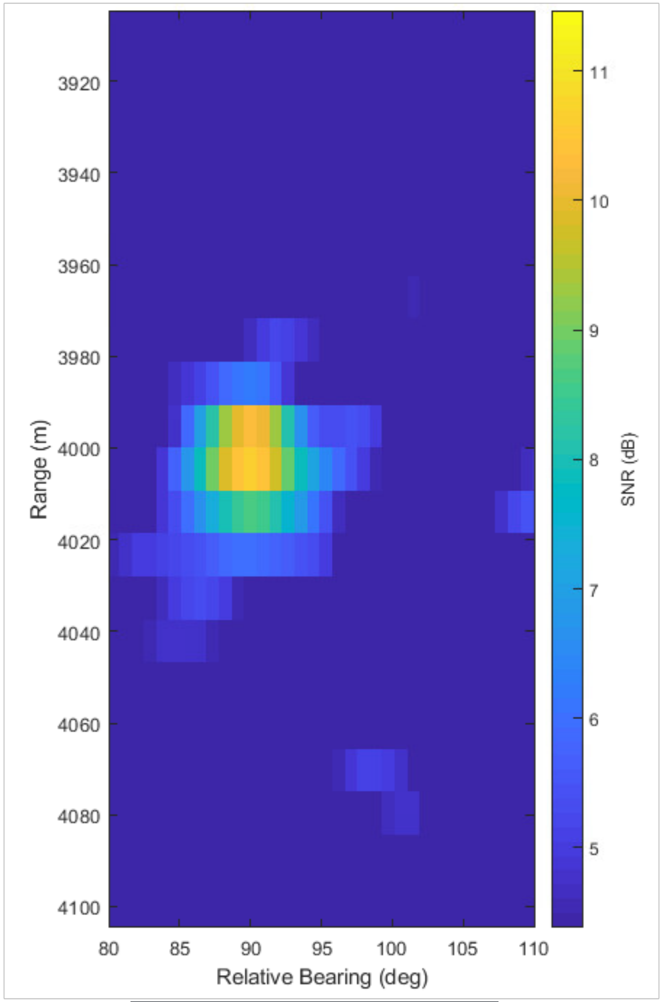


UNIVERSITY OF LIVERPOOL

National Oceanography Centre

TRACKING AND LOCALISATION

Tracking with real measurements



Sonar SNR data

Threshold

Cluster

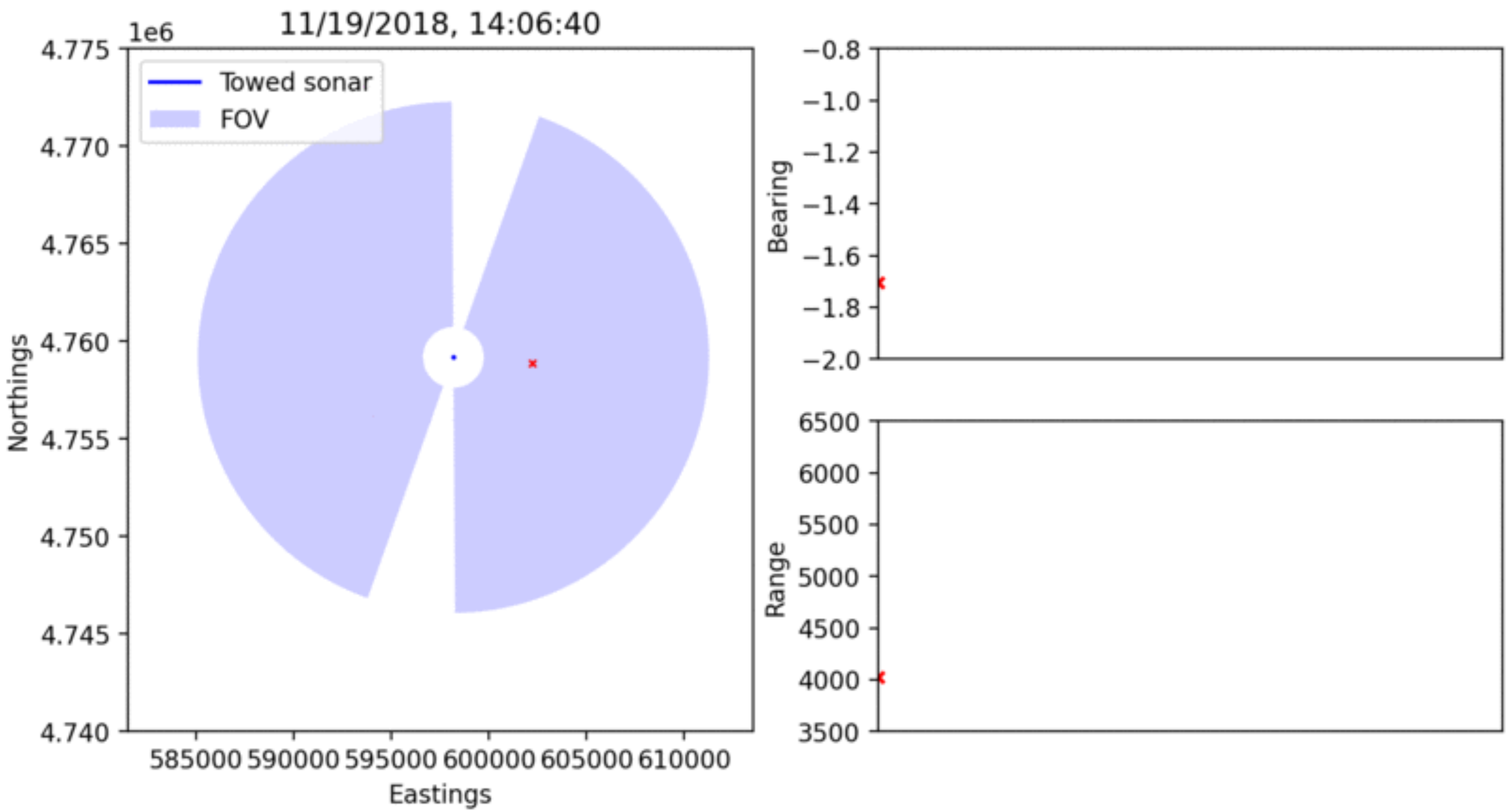
Extract [plots]

Track

UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Single target measurements



Measurement model

- Turning a sequence of extracted **plots** $y_{1:k}$ into a **track** $\hat{x}_{1:k}$ requires that the **measurement model** $h(\cdot)$ and **noise characteristics** are known to the filter.

- A standard model of bearing-range sensor located in s_k is given by

$$\begin{aligned} y_k &= h(x_k, s_k) + w_k, \\ &= \begin{bmatrix} \varphi(x_k, s_k) \\ r(x_k, s_k) \end{bmatrix} + w_k, \end{aligned}$$

where w_k is additive Gaussian noise with known covariance.

- In practice, the noise characteristics are unknown and determined by many factors:
  - **Internal**: own heading, Tx/Rx separation, platform motion, beamwidth, range-doppler ambiguity
  - **External**: speed of sound, sea surface/bed multipath reflections, reverberation

UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Computing noise statistics from data

$$y_k = \begin{bmatrix} \varphi(x_k, s_k) + \varphi_{bias} + \sigma_\varphi n_\varphi \\ r(x_k, s_k) + r_{bias} + \sigma_r n_r \end{bmatrix}$$

- One way is to involve a **known target** in $x_{1:N}$, so the noise statistics can be computed from $y_{1:N} = \{\varphi_i, r_i\}_{i=1}^N$ using

$$\varphi_{bias} = \frac{\sum_{i=1}^N (\varphi_i - \varphi(x_i, s_i))}{N} \text{ and } \sigma_\varphi = \sqrt{\frac{\sum_{i=1}^N (\varphi_i - \varphi_{bias})^2}{N}}.$$

- Otherwise, techniques like **expectation maximization** can be used

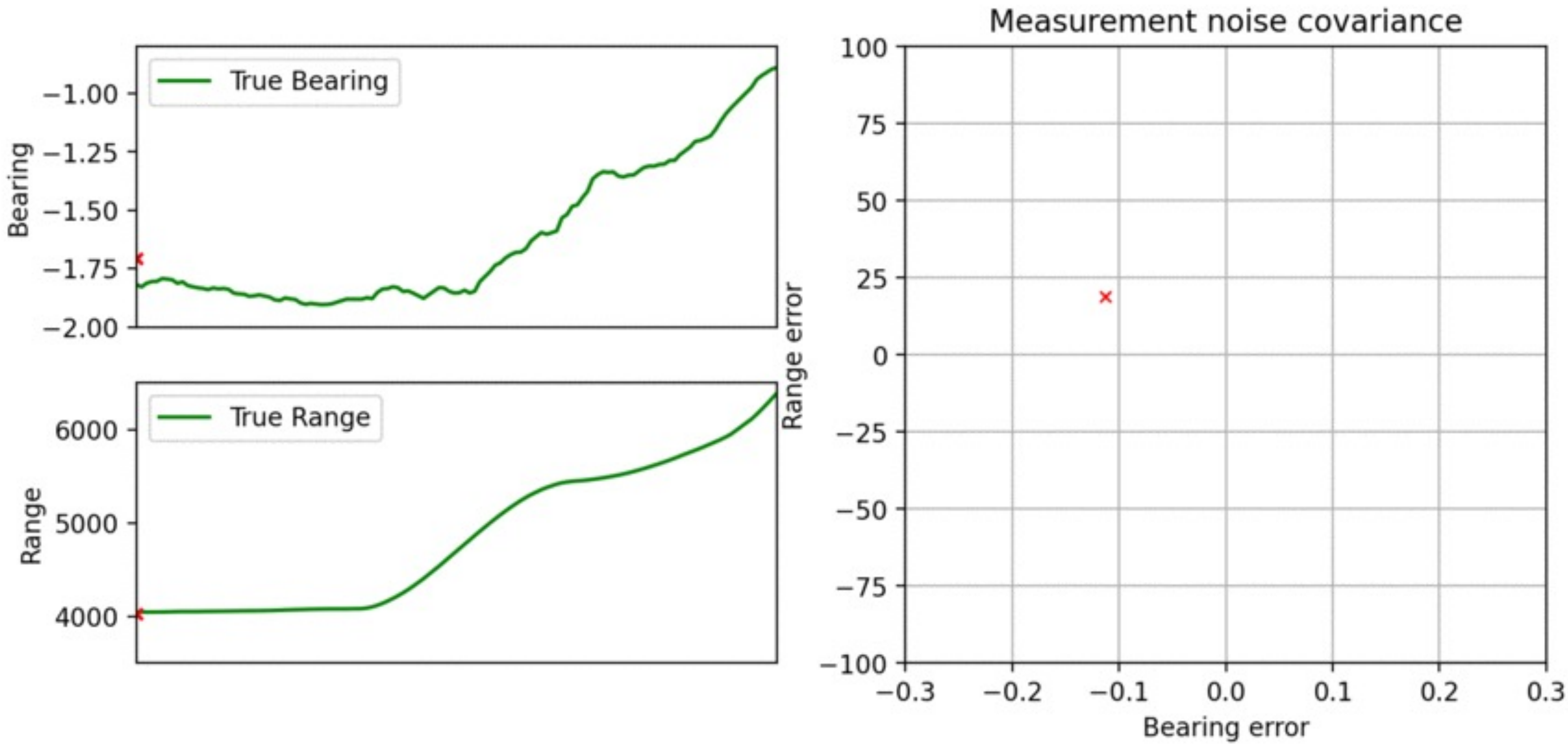
$$\theta^* = \arg\max \log p(y_{1:N} | \theta),$$

for a vector $\theta = [\varphi_{bias}, r_{bias}, \sigma_\varphi, , \sigma_r]^T$ of unknown parameters.

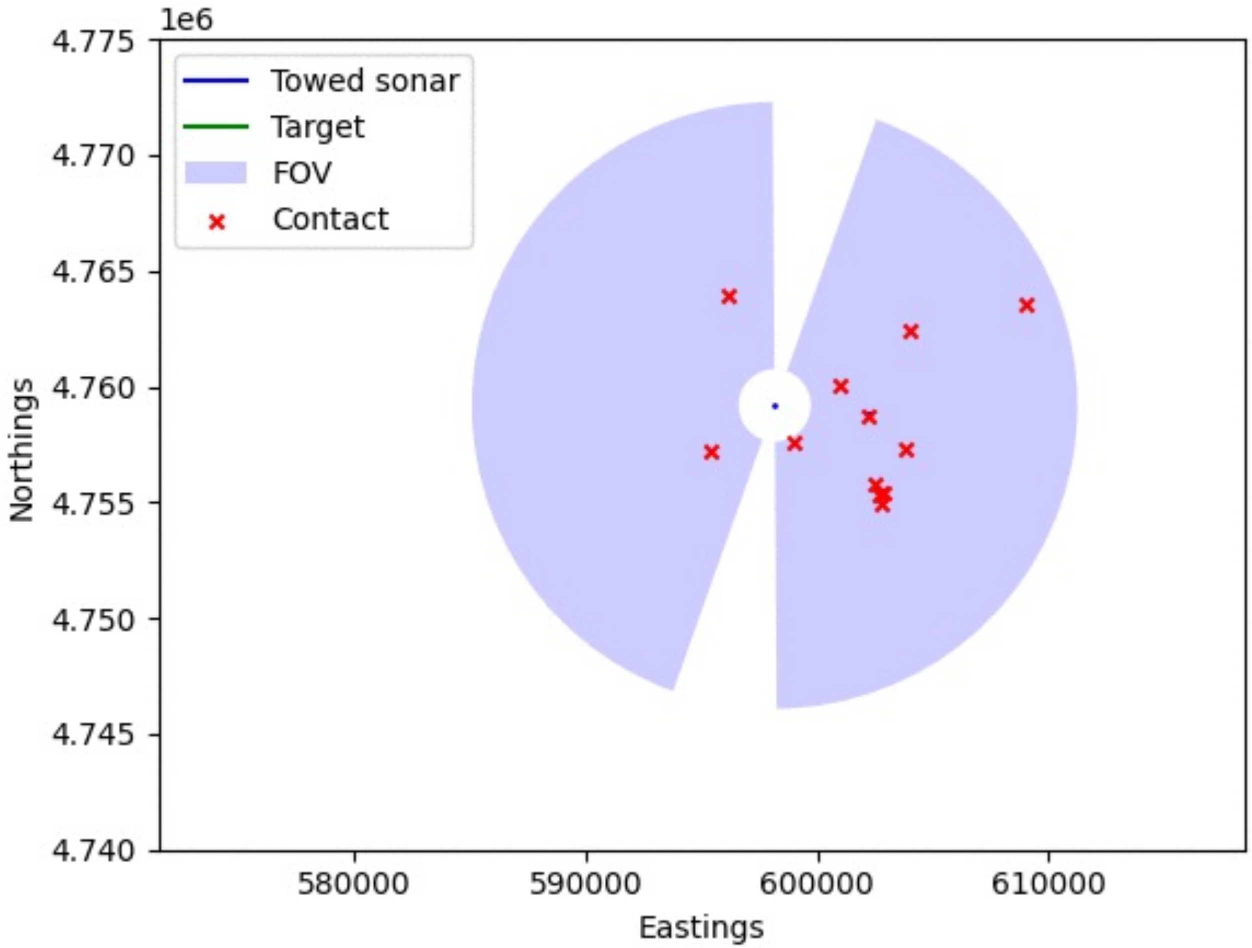
UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Obtaining noise statistics for a known target



Cluttered measurements in littoral environment

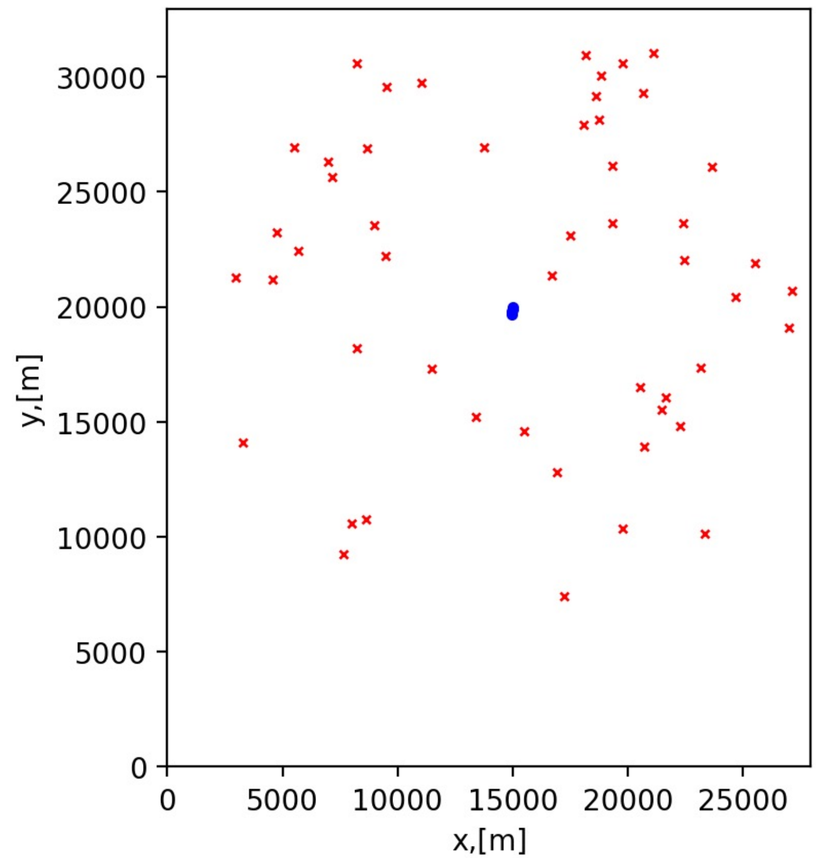


UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Stone Soup

- Stone Soup provides a collection of standard tracking algorithms for comparison
  - Simulation of an analogous scenario to understand how to ‘connect the dots’ in Stone Soup (green tracks over broad yellow truths)
  - Currently working on processing the real LCAS data in a compatible format



Stone Soup code base: https://github.com/dstl/Stone-Soup
Stone Soup Jupyter Notebooks: https://github.com/dstl/Stone-Soup-Notebooks
Stone Soup documentation https://stonesoup.readthedocs.io/
ISIF Open Source Tracking and Estimation Working Group https://isif-ostewg.org/
Stone Soup data: https://isif-ostewg.org/data
Stone Soup community forum https://gitter.im/dstl/Stone-Soup

UNIVERSITY OF LIVERPOOL

National Oceanography Centre

Summary

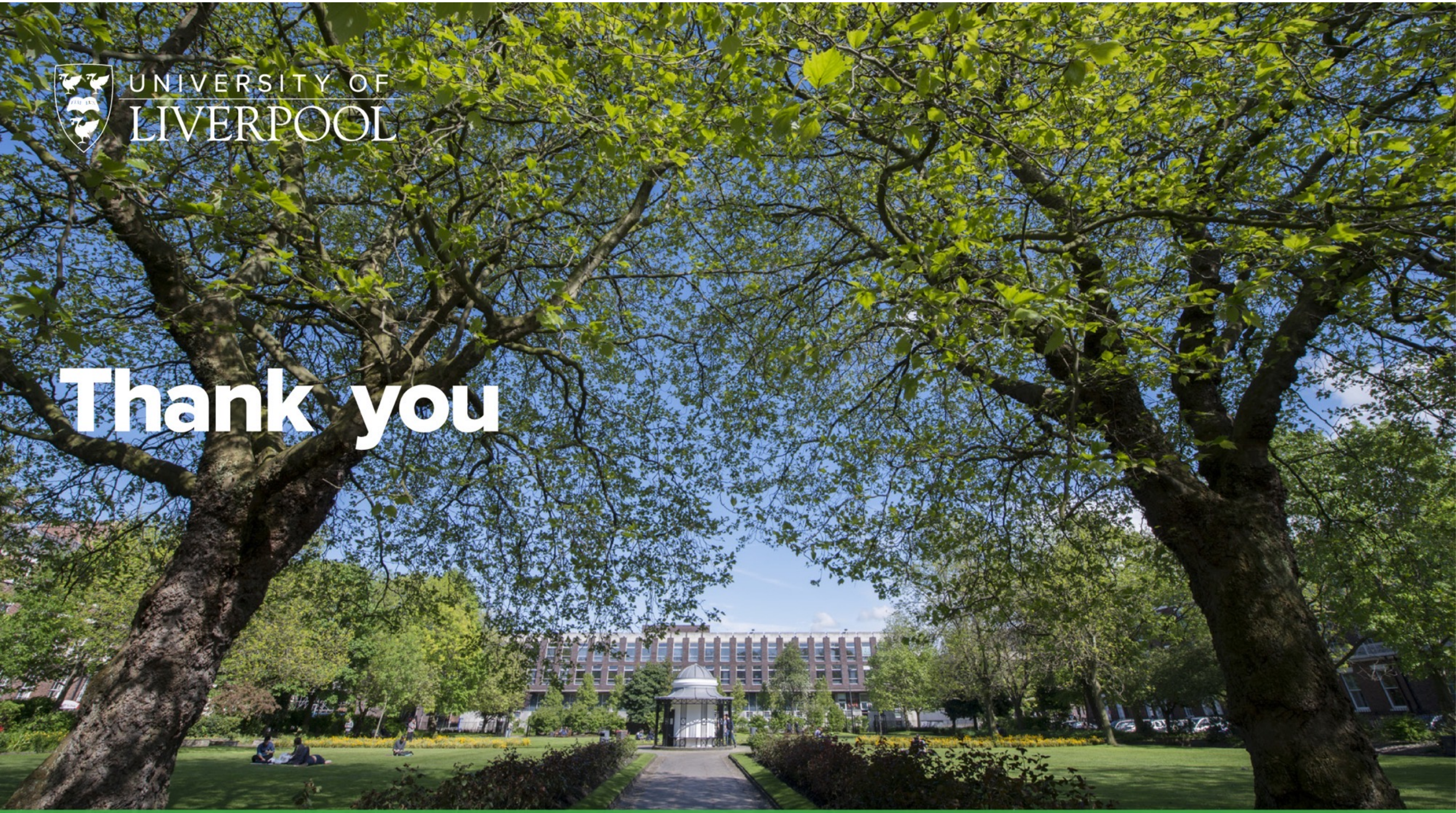
- Sonar processing is extremely challenging
  - Sonars cover a wide range of sensor types and applications
  - Propagation, noise and clutter are non-trivial
- **Beamforming** – Bayesian approach provides several advantages over standard beamforming techniques.
  - Generates an estimate of the DoA for the source of the energy in the signal, rather calculating the energy associated with each direction
  - Unaffected by issues such as sidelobes, and can combine uncertainties to reduce variance in the parameter estimates (θ, φ, M)
  - Robust to the effects of noise if the noise component is included within the model itself
- **Tracking** – Very high clutter levels and non-trivial sensor noise models
  - Tracking algorithms rely on the knowledge of measurement noise statistics
  - Statistics usually not known in practice, and are a function of many factors affecting the measurement process (both internal and external)
  - In principle, they can be extracted from data itself in case additional information is available to reduce the uncertainty

Further Work

- Beamforming:
  - Fusion of data from multiple narrowband frequencies
  - Application to more challenging settings involving a mix of both passive and active sonar
  - Using sequential Monte Carlo instead of MCMC to make full use of parallel processing capabilities (i.e. higher accuracy and precision in a shorter timeframe)

- Tracking:
  - Using Stone Soup trackers on cluttered data across several datasets (obtained through variation in the processing of received signals)
  - Tracking performance evaluation and comparison across the processing schemes

UNIVERSITY OF LIVERPOOL
National Oceanography Centre



Thank you

UNIVERSITY OF LIVERPOOL

National Oceanography Centre