Topographic Visual Analytics of Multibeam Dynamic SONAR Data

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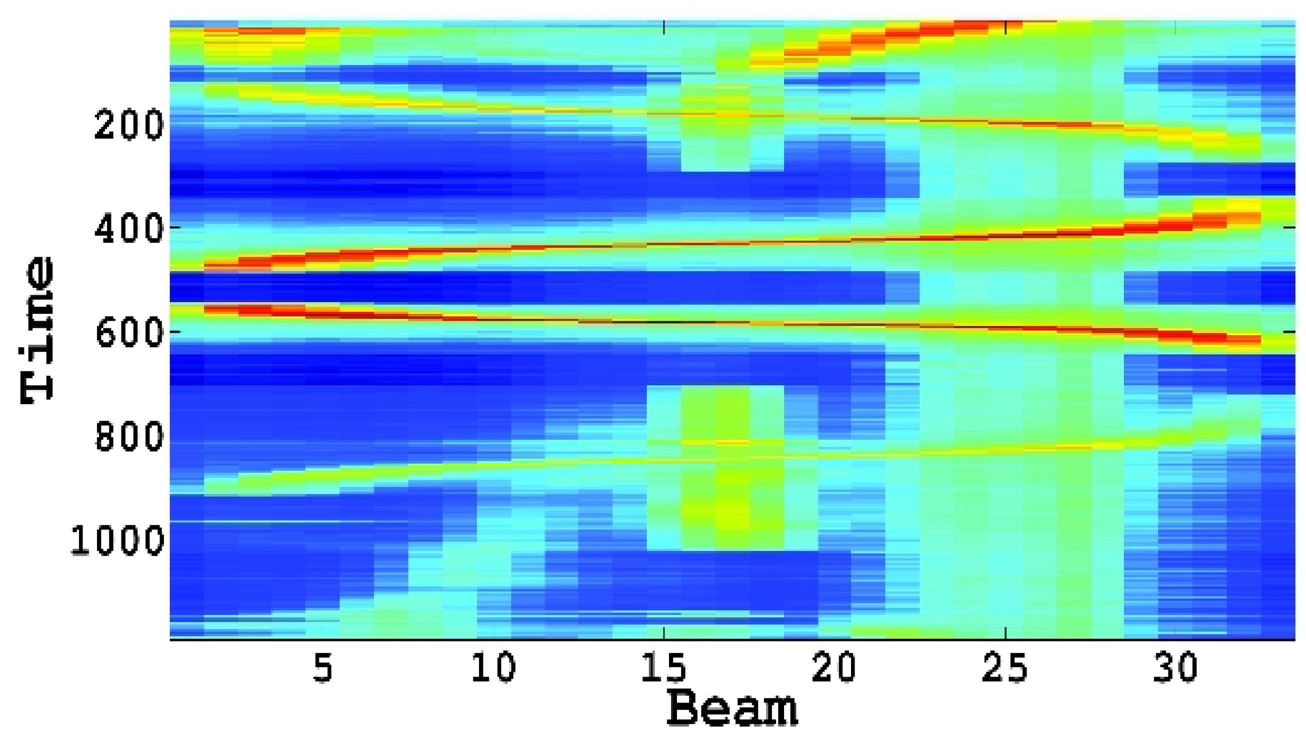
Domain Background:

- SONAR (sound navigation and ranging) has been used since the early 1900's
- SONAR types: *Passive* (listening to radiated sound) and *Active* (Projector generates a pulse and the returning echo is compared to the original pulse)
- Problems not faced in other signal processing domains (radar or speech analysis) which lead to high uncertainty, noise and non-linearity:
  - large amounts of clutter from unknown sources creating a low signal-to-noise ratio and high rates of false alarms in classification
  - high volume data analysis with sensors consisting of a large number of sensors
  - encompassing reflections from the sea bed, surface and refracted paths.
- SONAR Systems are working with high-dimensional, multimodal data requiring compression without data overload and analysed in real time by human operators

Data:

The data supplied by DSTL is a real world 32 hydrophone scenario where a speedboat travelled from end to end of the array in a shallow water environment. There was some ~50Hz noise present in all sensors, however there was no rain or shipping noise present. The broadband plot of the exercise is shown on the right.



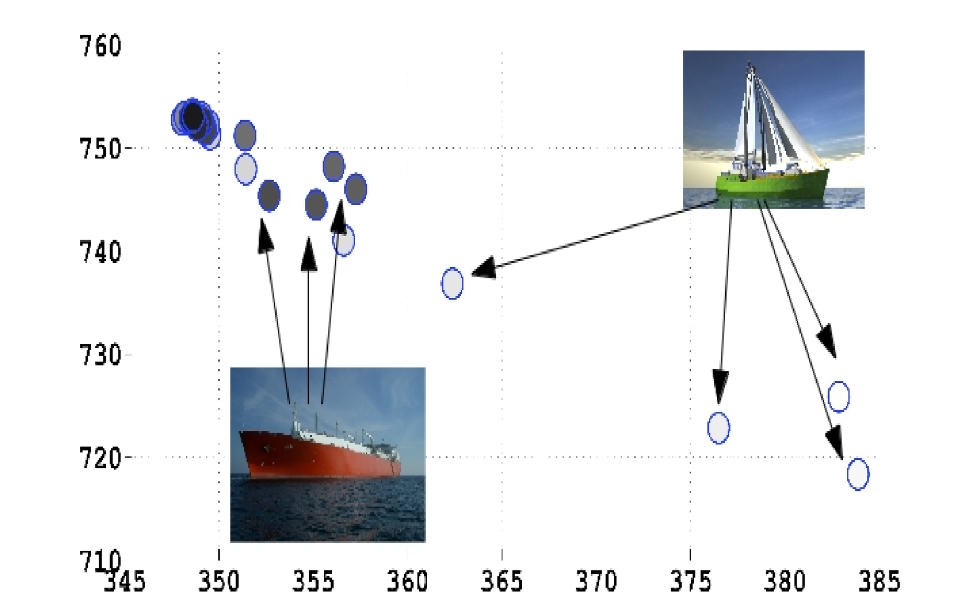
Beam Grouping Approach:

Beams are grouped in overlapping sections of 5 beams and modelled with a nonlinear vector autoregressive process using an RBF network:

$$S^g_t = f(S^g_{t-n:t-1}) + \varepsilon^g$$

As a proxy for a noise model we construct covariance matrices characterising the models:

$$\Sigma_g = \frac{1}{M-1}(S^g - \bar{S}^g)^T(S^g - \bar{S}^g)$$



In order to visualise this NVAR process we must specify d^*_{ij} so the model covariance is treated as being the covariance of a 5-dimensional Gaussian and the zero-mean KL divergence is used to compare the models between beams.

Topographic Visualisation:

To avoid the data overload problem we seek a visualisation of the observed data that is *topographic* – preserving neighbourhood relationships and global structure of input data. In a pointwise dimension reduction problem we seek to minimise the STRESS when creating points, **y**, to represent the high dimensional data, **x**.

$$E = \Sigma_{j>i}(d^*_{ij} - d_{ij})^2 \qquad d^*_{ij} = ||x_i - x_j||^2 \qquad d_{ij} = ||y_i - y_j||^2$$

The points, **y**, are created using a Radial Basis Function network, creating a feed forward mapping where new datapoints can be projected to a visualisation space.

$$y_i = \Sigma_j \lambda_j \varphi(||x_i - \mu_j||)$$

This deterministic approach to visualisation called NeuroScale was extended to include uncertainty where the visualised points, **y**, are replaced with distributions:

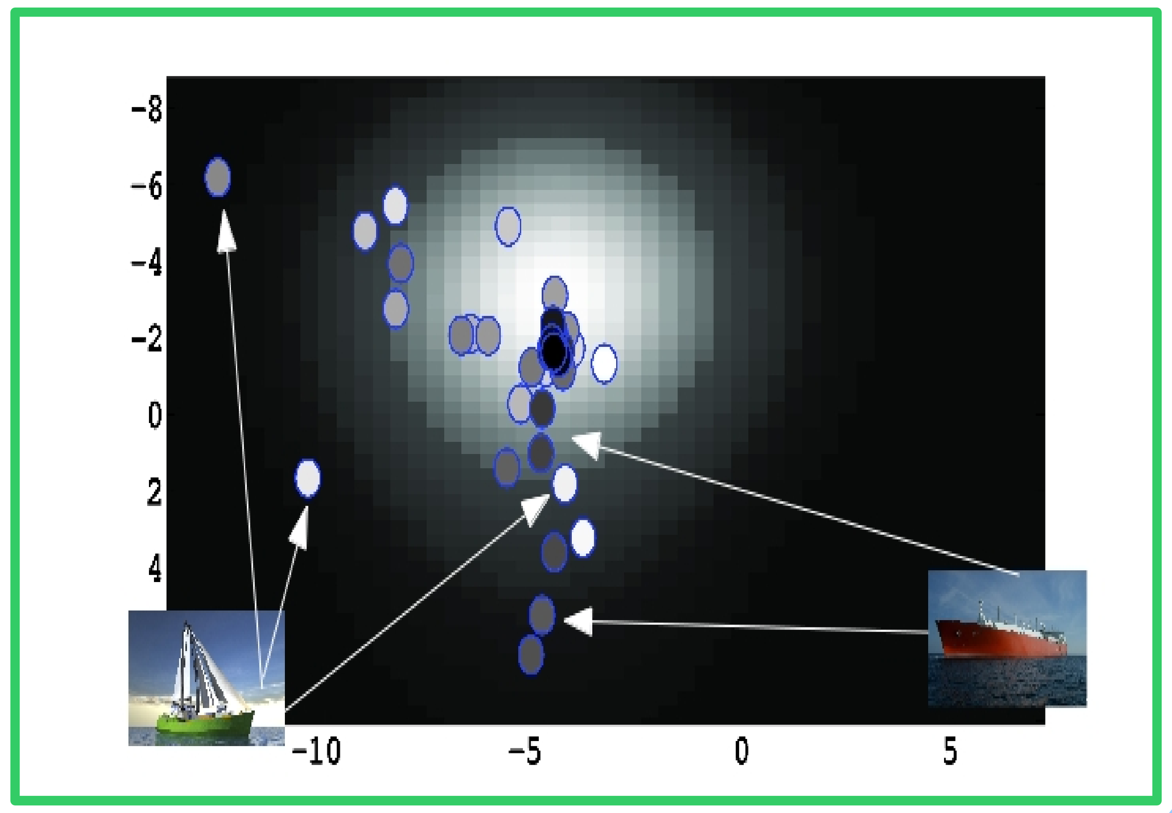
$$x \sim N(m,\sigma) \longrightarrow y \sim N(y,\sigma) \qquad d_{ij} = KL(y_i \,||\, y_j)$$

Beam by Beam Approach:

The target signal is modelled as a periodic nonlinear auto-regressive signal of order 14 estimated by an RBF Neural Network. The residuals, $|\mathbf{x} - \bar{\mathbf{x}}|$, are modelled by a realistic noise mixture model.

Laplace (other signals)	+	Rayleigh (thermal)	+	Gamma (rain)	+	K (reflections)	+	Gaussian (residuals)

The beam **dissimilarity** is the sum of the target signal and noise dissimilarity measures. The target signal dissimilarity compares the PSD of the predictive RBF model above and the noise dissimilarity compares overlap of the PDFs using the Bhattacharyya distance. The variance of the noise mixture is then treated as the uncertainty used as the variance when constructing each visualised Gaussian distribution, **y**, creating a 33 component GMM visualisation space.



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Aston University Supervisors: Professor David Lowe and Professor Ian Nabney