



National Physical Laboratory

Sensor network topics

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Bath SAMBA ITT, 29th January – 2nd February

Outline

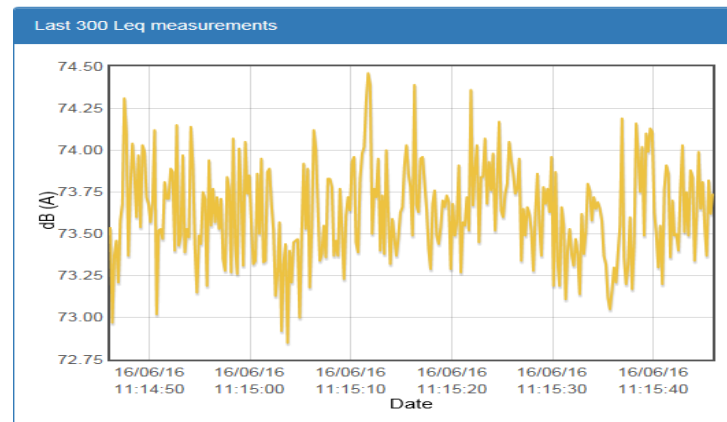
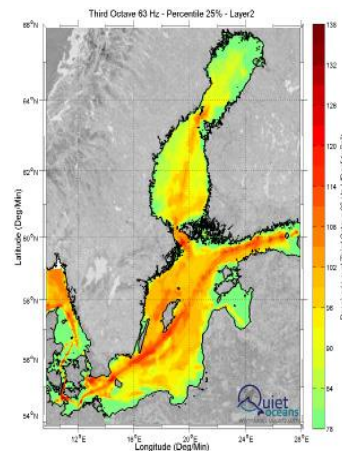
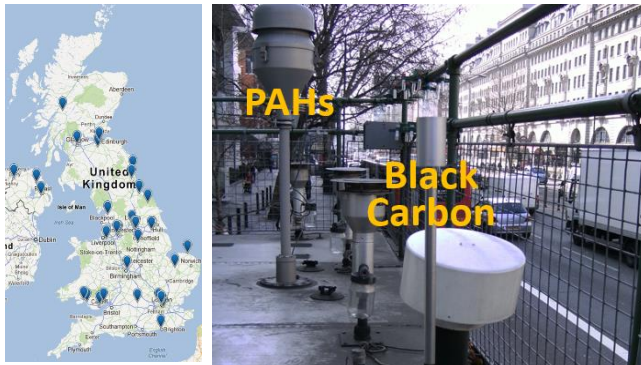
- Background
- Three topics
 - Prediction under uncertainty
 - Source identification and tracking
 - Network design
- Available data
 - Real acoustic sensor network data
 - Software to simulate sensor network data

Sensor networks

- Collection of (often) many low-cost sensors making discrete measurements (in space, time and frequency) of quantities that vary continuously (in space, time and frequency)
- Can operate at different scales (factory, neighbourhood, city, region, global)
- Source of large volumes of data
- Want to use data to make predictions and decisions, for source identification and attribution, all supported by statements of uncertainty

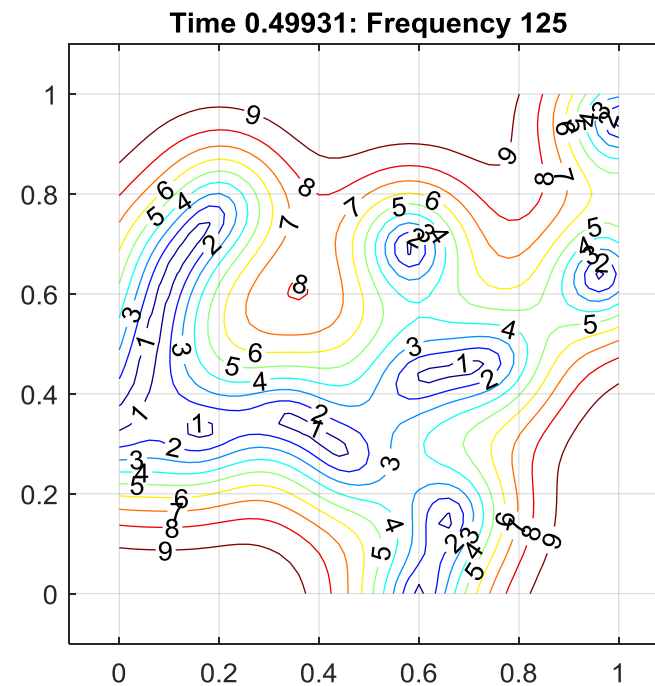
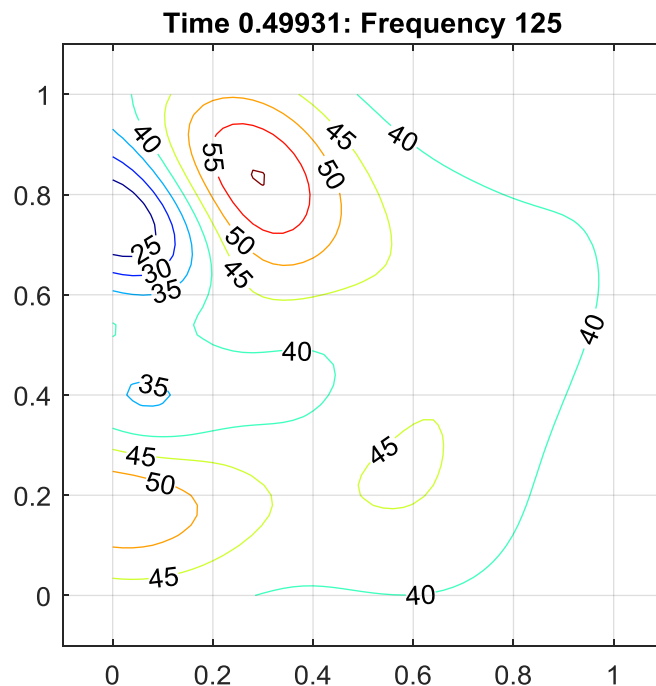
Examples

- Underwater acoustic noise in oceans
- Air quality and airborne noise in urban environments
- Radiometric measurements from satellites for EO



Prediction problem

- Create spatial-temporal-frequency maps of both estimates and uncertainties for measured quantities
- For single sensor network or sensor networks co-located and operating with different modalities (measuring different quantities that are dependent)



Prediction problem

- GPs are a useful tool but challenging to apply when the size of the training set exceeds a few thousand

Example of airborne acoustic network provided 500,000 measured values per day

- Given training set (X, y) , a GP with covariance function $k(x_1, x_2)$, and noise variance σ_n^2

$$y_* = K(X_*, X)[K(X, X) + \sigma_n^2 I]^{-1} y,$$

$$\text{cov}(y_*) = K(X_*, X_*) - K(X_*, X)[K(X, X) + \sigma_n^2 I]^{-1} K(X, X_*)$$

Requires solution of large symmetric systems of equations

Prediction problem

- Learning about parameters of covariance function and σ_n^2 by maximising log-likelihood

$$\log p(y|K, \sigma_n^2) \propto -\frac{1}{2} y^T [K(X, X) + \sigma_n^2 I]^{-1} y - \frac{1}{2} \log |K(X, X) + \sigma_n^2 I|$$

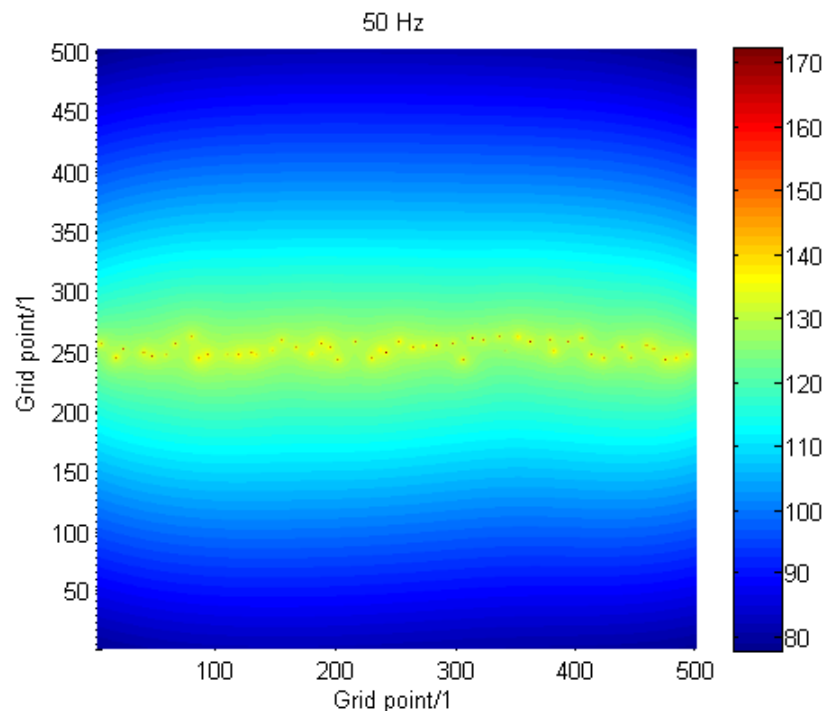
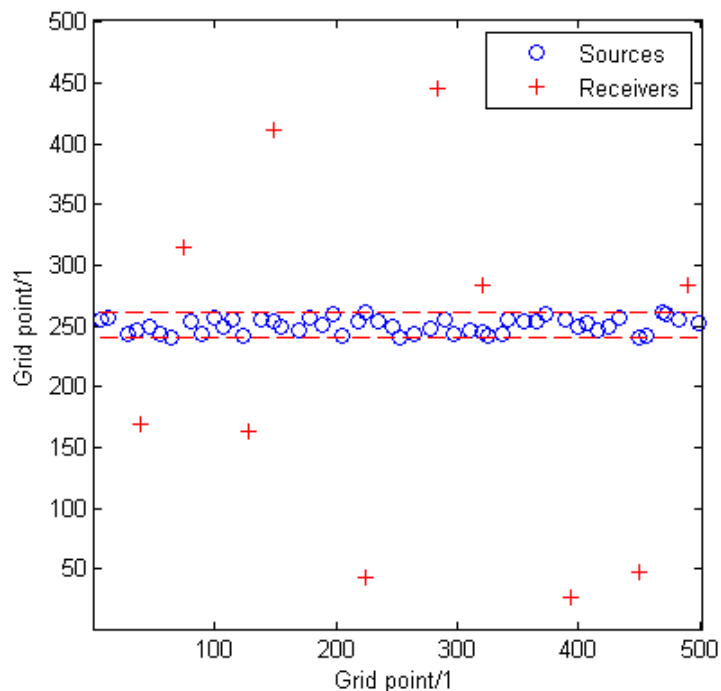
Evaluation also requires eigenvalues of large symmetric matrix

- Exploit structure of data (gridded) and structure of covariance function (separable) to decompose matrices as tensor matrix products ... then, e.g., combine with iterative methods to solve equations
Copes with large problems but computations are slow

Source identification and tracking problem

- Add knowledge that the measured quantity depends on a small number of sources and a model for how the quantity varies with distance from a source

For an acoustic problem, this could be a model of propagation loss



Source identification and tracking problem

- For a single time instant, vector s represents source factors at possible source locations
- Find solution $s \geq 0$ to minimize

$$\|As - y\|_2^2 + \tau \|s\|_1$$

First term matches model to sensor observations y : highly under-determined system: maybe ~ 100 observations but $\sim 10,000$ unknowns

Second term regularises solution by forcing sparsity

Parameter τ used to control balance between “fitting” data and level of sparsity

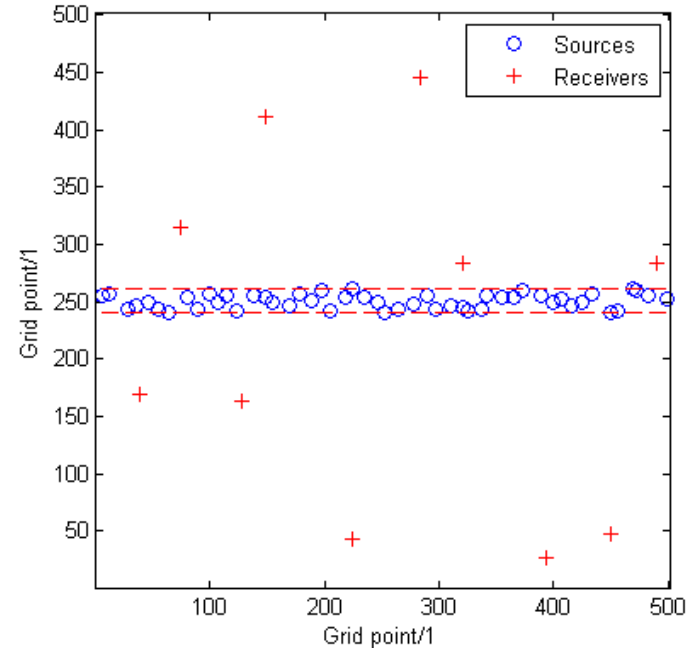
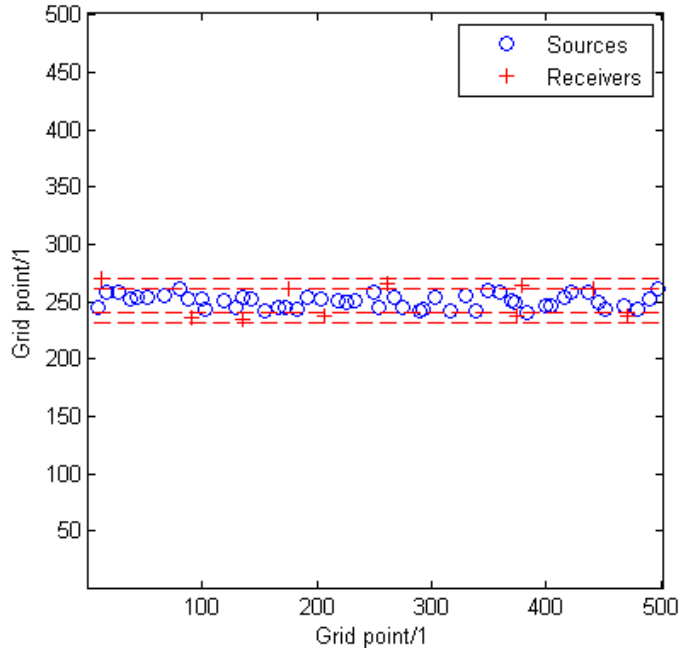
Columns of design matrix A are highly coherent, which limits the “spatial resolution” to which the source locations can be estimated

Source identification and tracking problem

- Account for additional knowledge that locations of some of the sources are known (from GPS transponder data), but not their source levels
- Use knowledge of the precision of the sensors to provide uncertainty evaluation
- Use data recorded at consecutive times to track sources
 - The sources can be expected to move along continuous paths ... initially straight-lines ... and to have a constant source level
 - Real-time solution in the form of a filter?

Design problem

- To deploy a sensor network, need to decide
 - Number of sensors
 - Locations of sensors
 - “Quality of sensors”: short-term (noise characteristics) and long-term (drift characteristics)



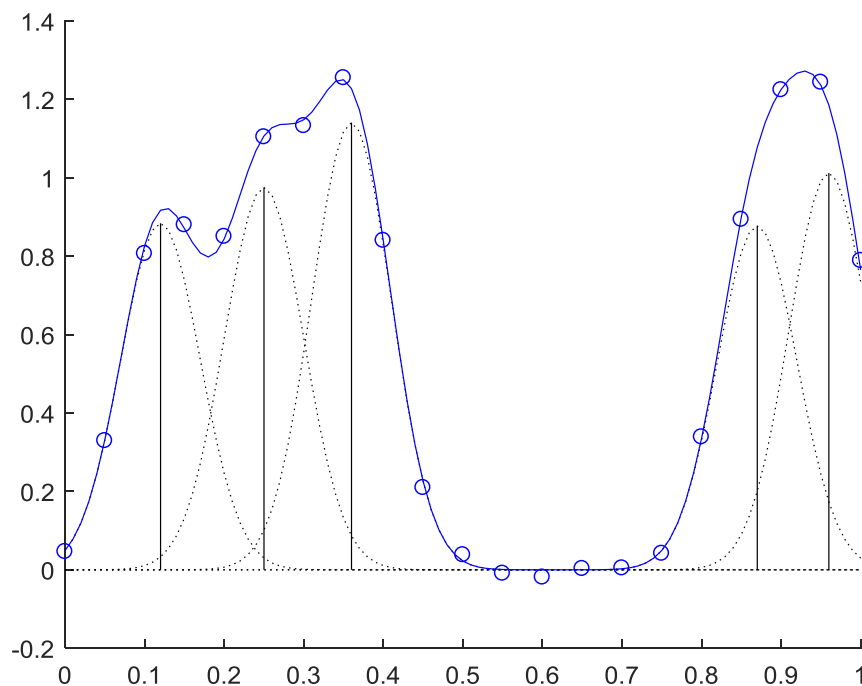
Design problem

- Optimise a measure of information (gain)
 - E.g., trace of covariance matrix for predictions made at a number of spatial locations
- But balanced against constraints
 - On cost (dependent on number and quality of sensors)
 - On where the sensors may be located (e.g., shipping lane is inaccessible)
- May also be a design specification
 - Requirement to make a prediction that meets a target uncertainty

Data

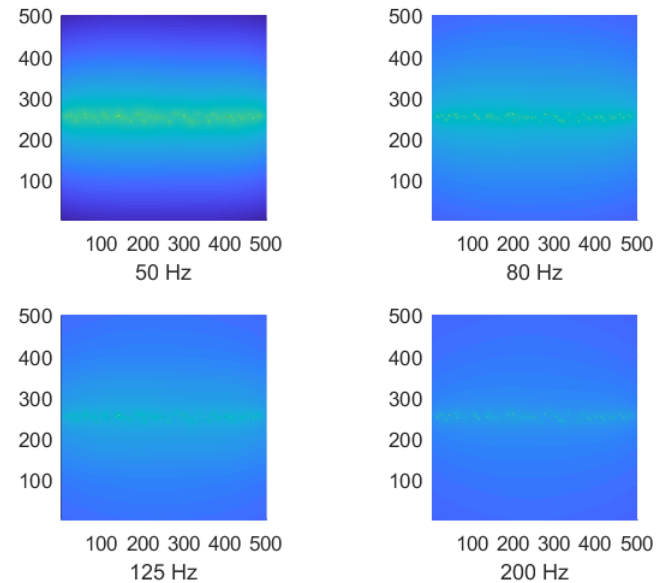
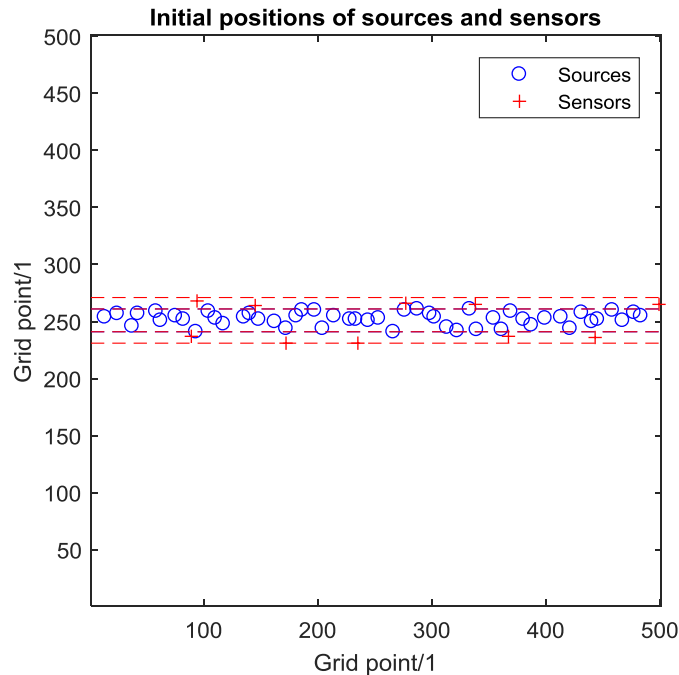
- Real acoustic sensor network data
 - 17 sensors at known locations (longitude and latitude), but sensor 9 recorded no data
 - Each sensor makes a measurement every minute
 - Each sensor records sound level at 26 frequencies (also aggregated into single broadband level)
 - Data for 8 consecutive days (in 8 separate files)
- Two spatial variables, temporal variable and can choose to ignore log-frequency variable (by using broadband level)
- Drop-outs in data (treated as missing values)

Simulation with single spatial variable



- Control number of sources, locations and source levels
 - Control number of sensors, locations and noise variance
 - Control Gaussian propagation loss function
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- Matlab script to simulate matrix A and measurement vector y , and runs LASSO and Bayesian LASSO

Simulation with two spatial, temporal and frequency variables



- Extended to two spatial variables, temporal and frequency variable, with (more) realistic propagation loss function
- Matlab script to simulate design matrix A and measurement vectors y (as sources move)



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FUNDED BY BEIS

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