



monitoring the future



with the next
generation
of sensors



Conference Paper #09

Acoustic camera created using a distributed optical fibre –based sensor



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Overview



- Introduction to Silixa and distributed sensing**
- Experiment overview**
- Signal processing approach**
- Results**



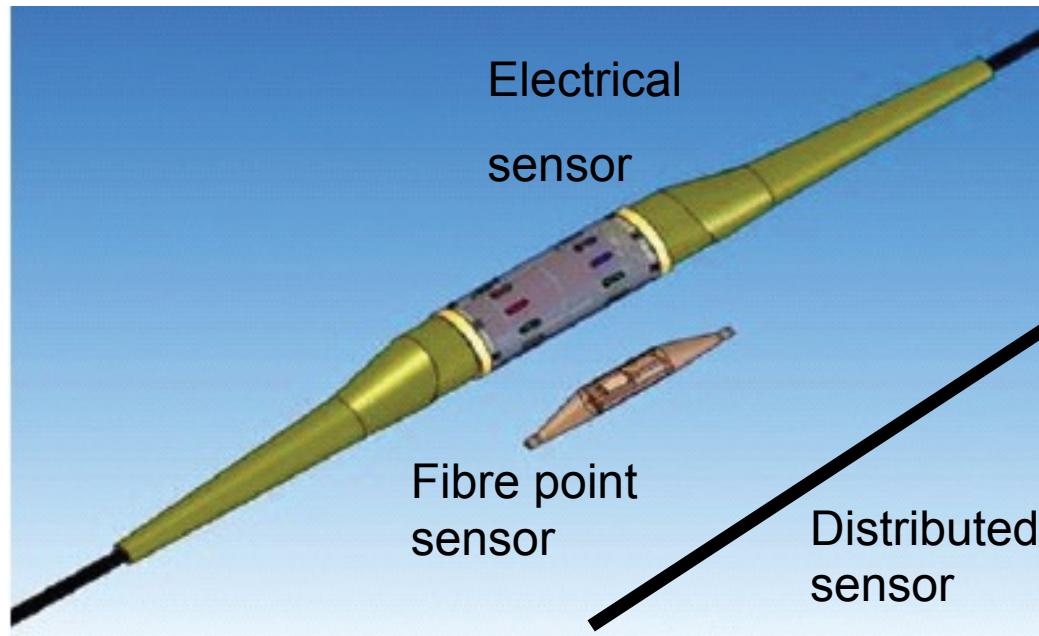
Introduction to Silixa

Fibre optic based distributed sensing



Distributed & Point sensing comparison

- Continuous sensing cable
- Complete coverage
 - measurement every 1m along the entire cable length
- small size, flexible and cost-effective



iDAS

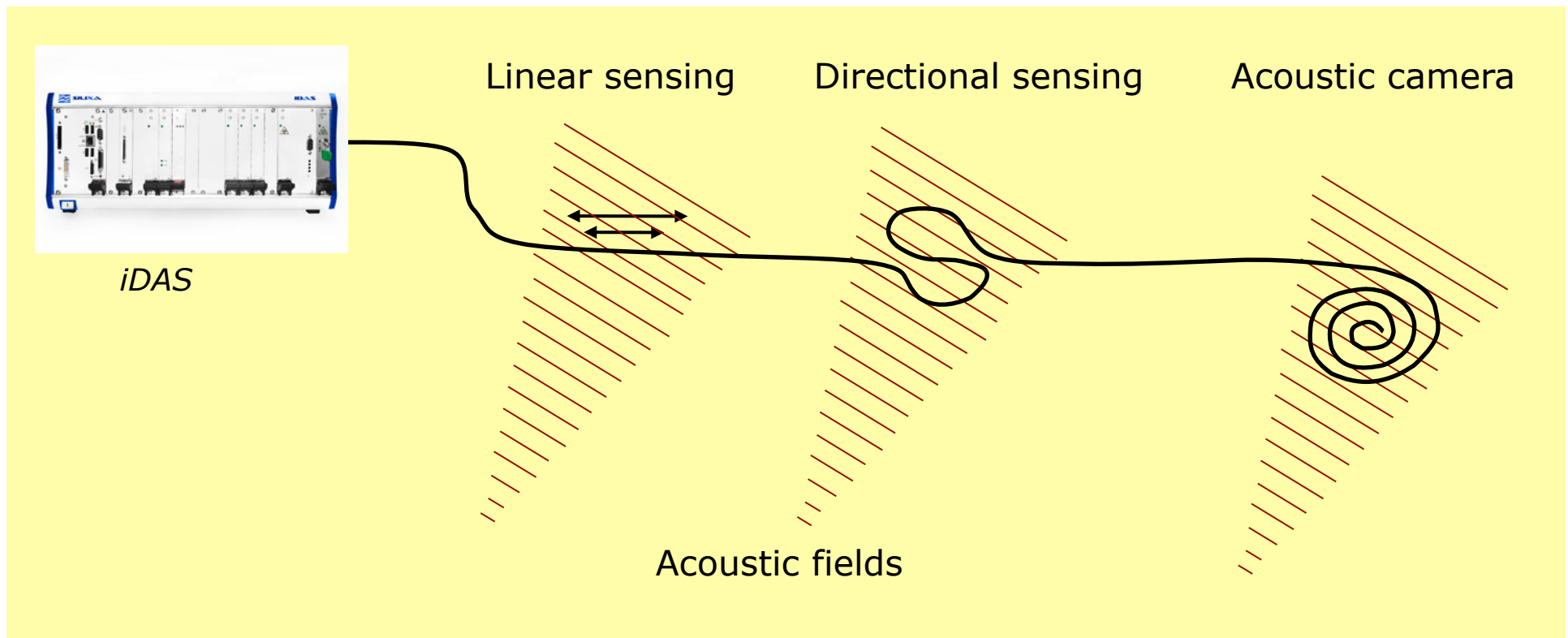
intelligent Distributed Acoustic Sensor



- » Simultaneous measurement of acoustic amplitude, phase and frequency at every metre along fibre
- » No cross talk
- » 90 dB dynamic range
- » *Acoustic sensing array*

Measuring sound is just the beginning!

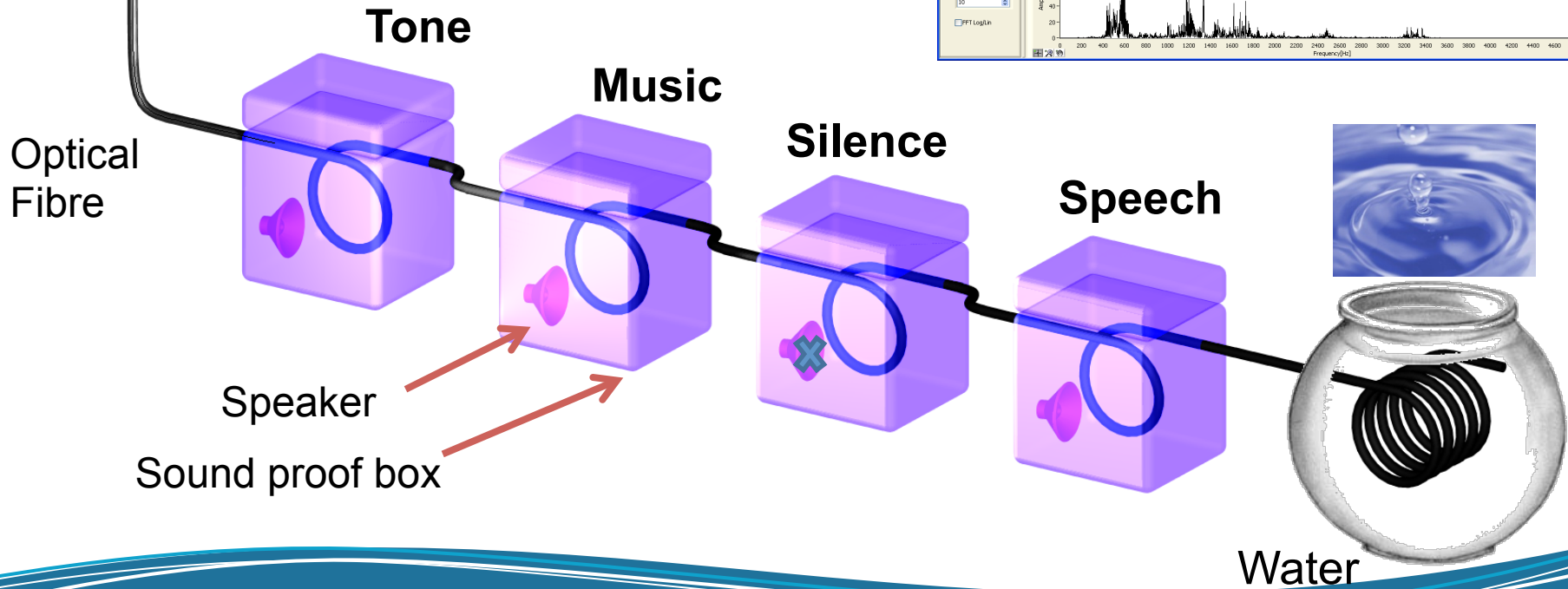
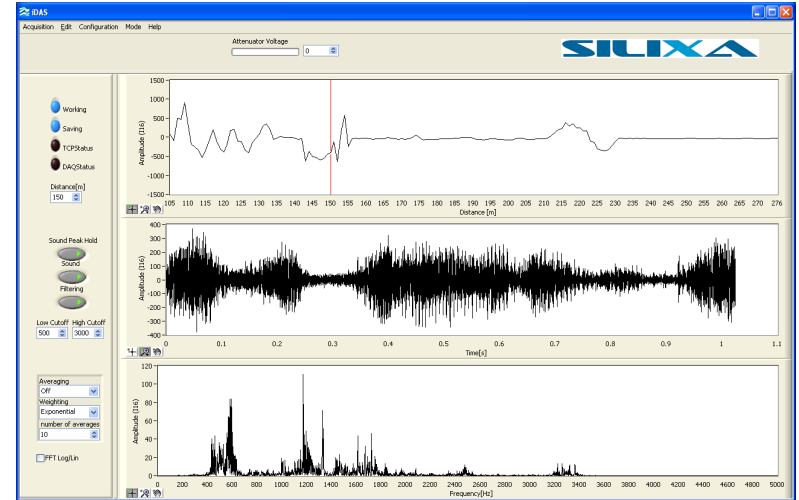
- Different fibre arrangements lead to a multitude of sensing opportunities
- For example, combining data from multiple points (which are all synchronised) allows beamforming to image the acoustic field far from the sensing fibre (e.g. acoustic camera/ telescope)

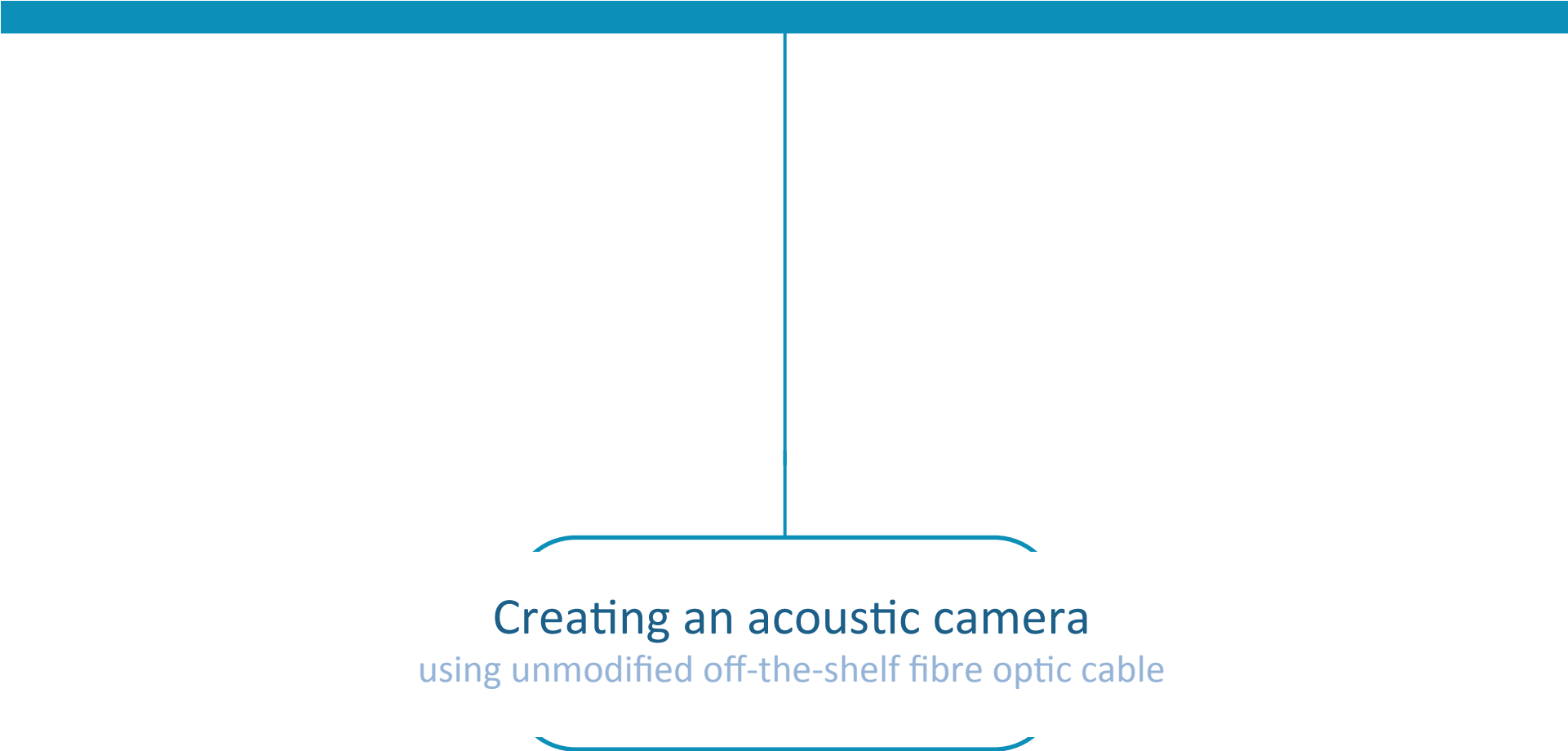


SILIXA *i*DAS Demonstration



SILIXA
*i*DAS Unit

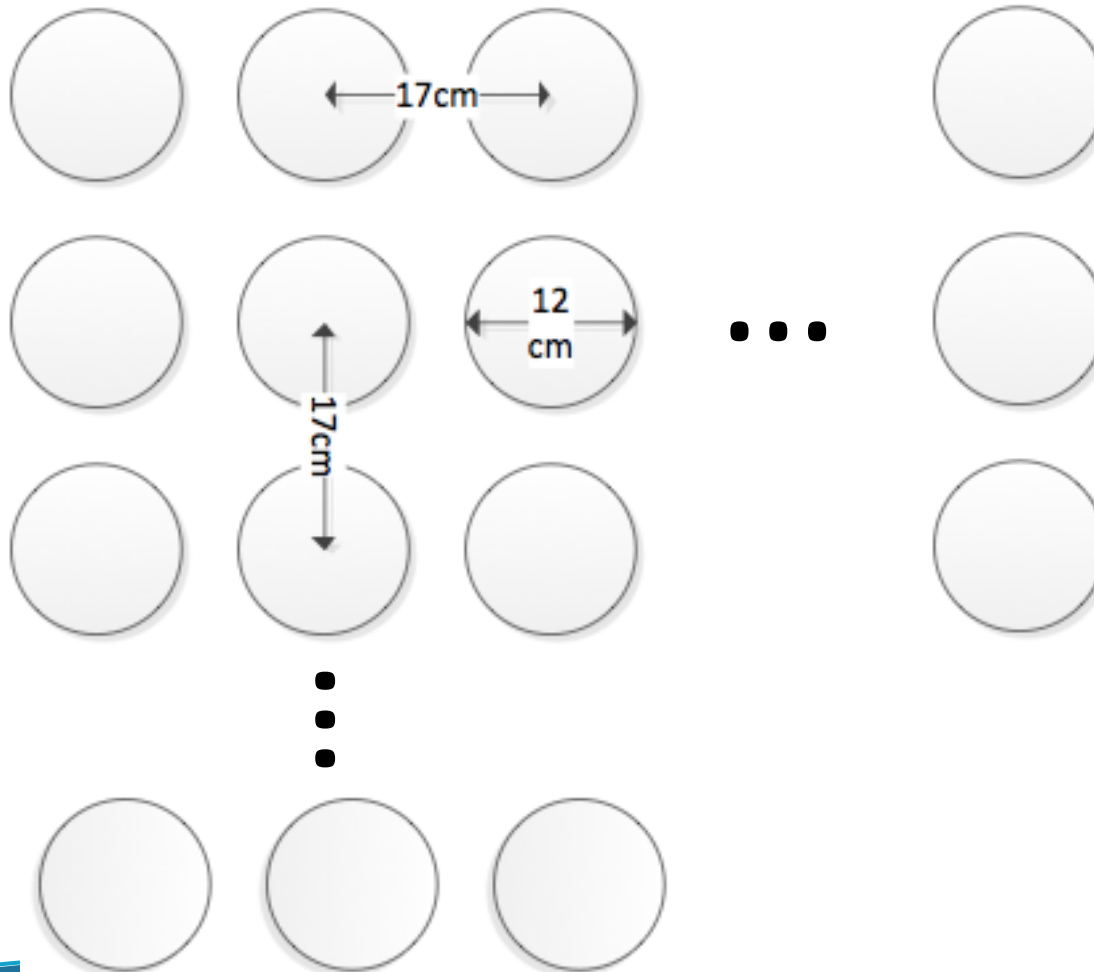


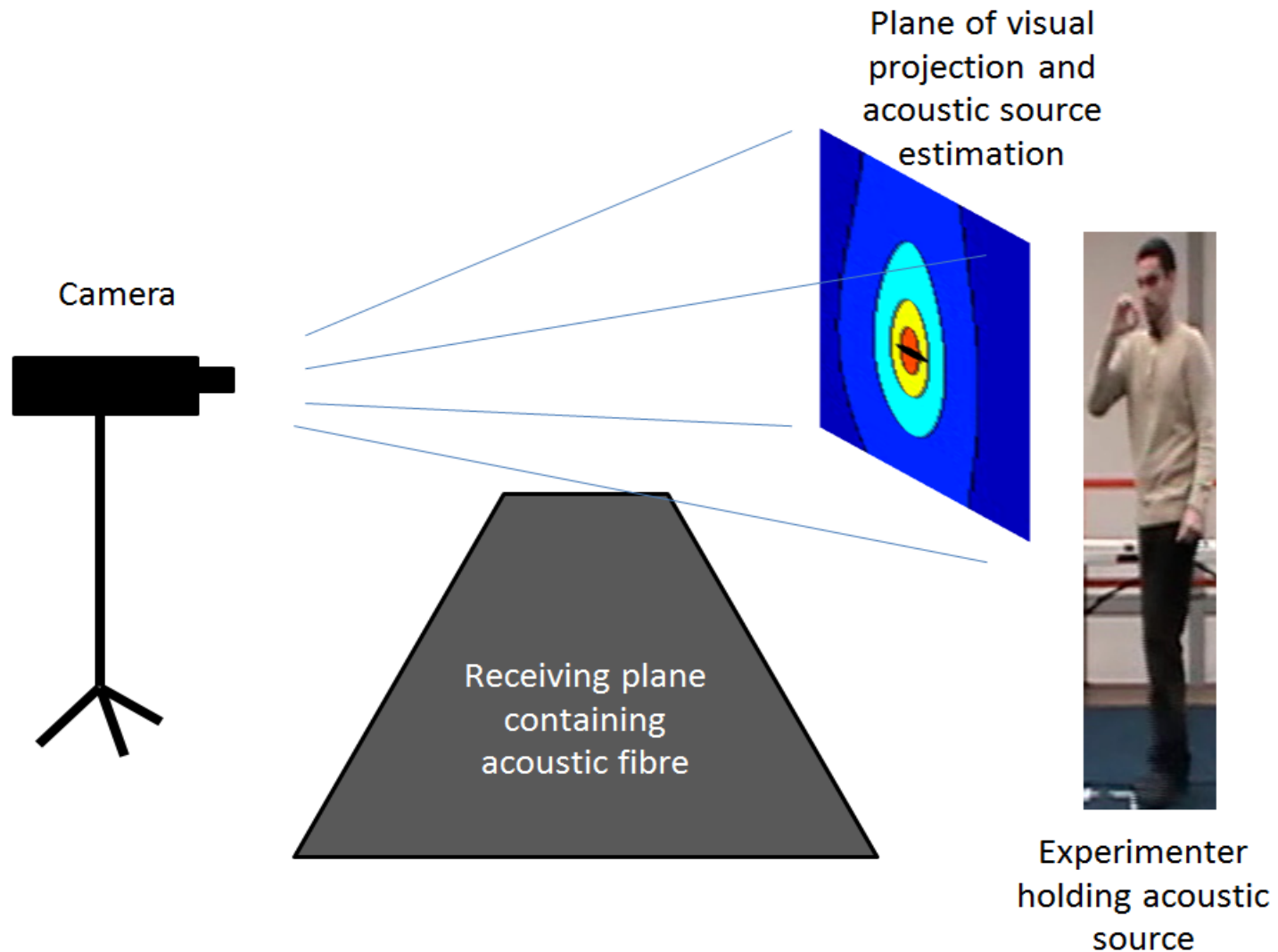


Creating an acoustic camera
using unmodified off-the-shelf fibre optic cable



Experiment Overview







Signal processing methodology

This approach can be implemented in real time





Signal Model



- Assuming that there are M narrowband sources with the same frequency for far field, the signal at the array can be modelled as:

$$\underline{x}(t) = \sum_{i=1}^M \underline{a}(\underline{r}, \theta_i, \phi_i) m_i(t) + \underline{n}(t)$$

where $\underline{a}(\underline{r}, \theta_i, \phi_i)$ is the manifold vector associated with the i th source and can be modelled as

$$\underline{a}(\underline{r}, \theta_i, \phi_i) = e^{j\underline{r} \cdot \underline{k}(\theta_i, \phi_i)}$$

- The direction of arrival of the incoming signals can be estimated using different methods
- Subspace methods (e.g. MUSIC, ESPRIT) are considered as high resolution DOA estimation techniques
- If sources are moving, the direction of arrival of the signals will change with time and hence the manifold vector is considered to be a slow varying function of time. Estimates from different time intervals have to be associated together in a multitarget environment. These estimates have to be smoothed.



Direction of Arrival Estimation

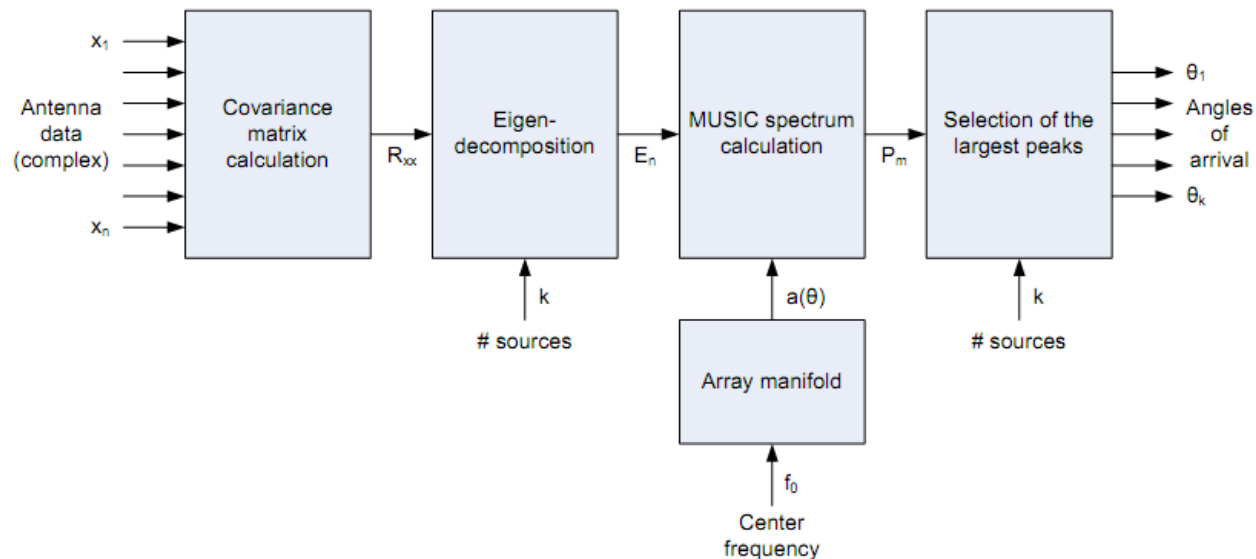


- The Multiple Signal Classification (MUSIC) algorithm is chosen for its high accuracy and simplicity. It is based on the formulation of the covariance matrix:

$$\begin{aligned}\mathbf{R}_{xx} &= \mathbf{E}\{\underline{x}(t)\underline{x}(t)^H\} \\ \mathbf{R}_{xx} &= \mathbf{R}_{sig} + \mathbf{R}_{noise}\end{aligned}$$

- The MUSIC algorithm utilizes the eigenstructure of the covariance matrix to estimate the direction of arrival.
- In particular, it uses the fact that the rank of the \mathbf{R}_{sig} matrix increases with increasing number of signals. Thus, assuming that the number of sources M is known, the eigenvectors corresponding to the minimum $N - M$ eigenvalues \mathbf{E}_n are orthogonal to the signal manifold vectors
- The MUSIC spectrum is formed by utilizing this orthogonality and searching over the following cost function:

$$z(\theta, \phi) = \frac{1}{\underline{a}(\underline{\mathbf{r}}, \theta, \phi)^H \mathbf{E}_n \mathbf{E}_n^H \underline{a}(\underline{\mathbf{r}}, \theta, \phi)}$$



- The MUSIC algorithm fails when signals are perfectly correlated (multipath) the rank of the signal covariance matrix R_{sig} reduces. To restore the rank of the matrix, spatial smoothing techniques are used to modify the covariance matrix.
- Spatial smoothing technique is therefore used. Spatial smoothing is based on preprocessing the array response by partitioning the array of sensors into subarrays and generate the average of the subarray covariance matrices



Tracking – Particle Filtering



- A state space model is defined for the i th target consisting of an azimuth θ and elevation ϕ

$$\begin{aligned}\underline{z}_i(k+1) &= \underline{z}_i(k) + \underline{\dot{z}}_i(k)T + \underline{w}(k) \\ \underline{z}_i(k) &= [\theta_i(k) \phi_i(k)]^T\end{aligned}$$

- The noise in the state space model is assumed to follow Gaussian distribution with a standard deviation of 5 degs. The movements in the azimuth and elevation directions are assumed to be uncorrelated.
- The measurement model is the output of the MUSIC algorithm which is assumed to be corrupted with a Gaussian noise as well with a standard deviation of 5 degs.

$$\underline{y}_i(k) = \underline{z}_i(k) + \underline{e}_i(k)$$

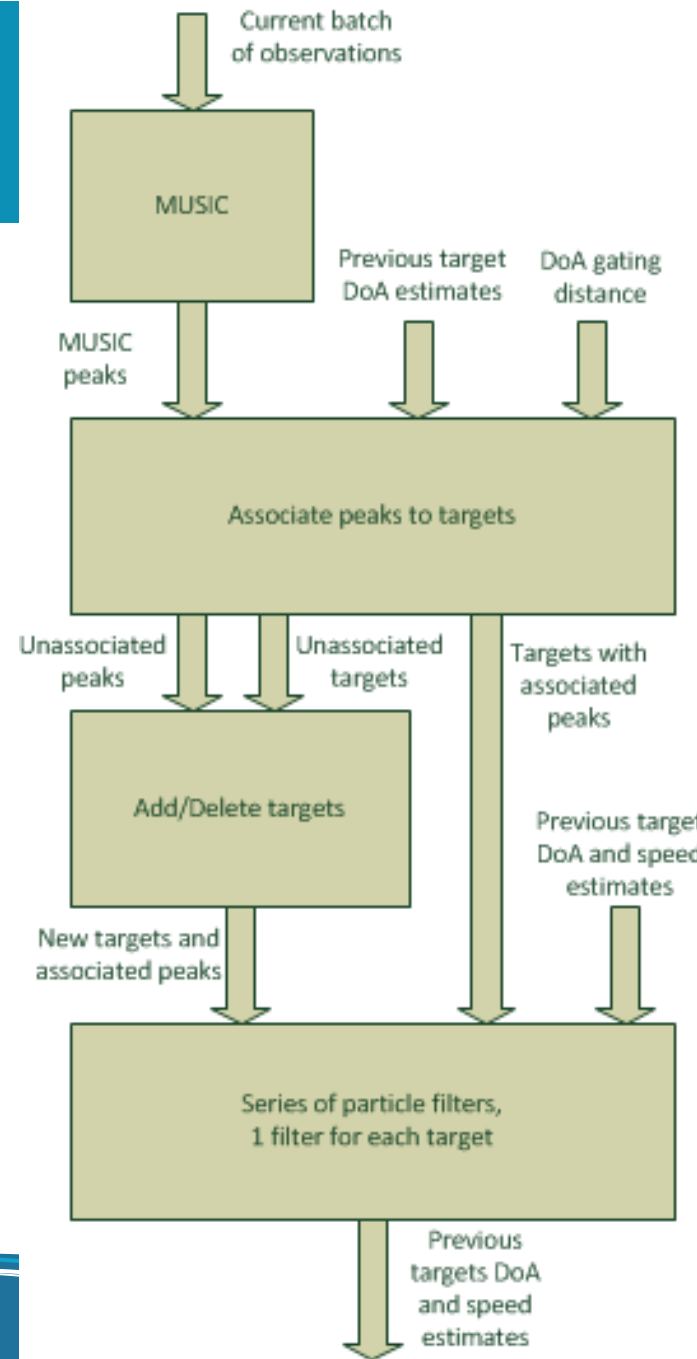
- The idea behind particle filtering is to represent the posterior density function by a set of random samples with associated weights and to compute estimates based on these samples and weights

$$p(\underline{z}_i(k) | \underline{y}_{i,l}(0:k)) = \sum_{n=1}^{N_s} v_{n,i}(k) \delta(\underline{z}_i(k) - \underline{z}_i(k)^n)$$

for $l = 1, \dots, L$ MUSIC peaks for the i th target

- The weights are chosen to be updated using the following

$$v_{n,i}(k) \propto v_{n,i}(k-1) p(\{\underline{y}_{i,l}(k)\} | \underline{z}_i(k)^n)$$

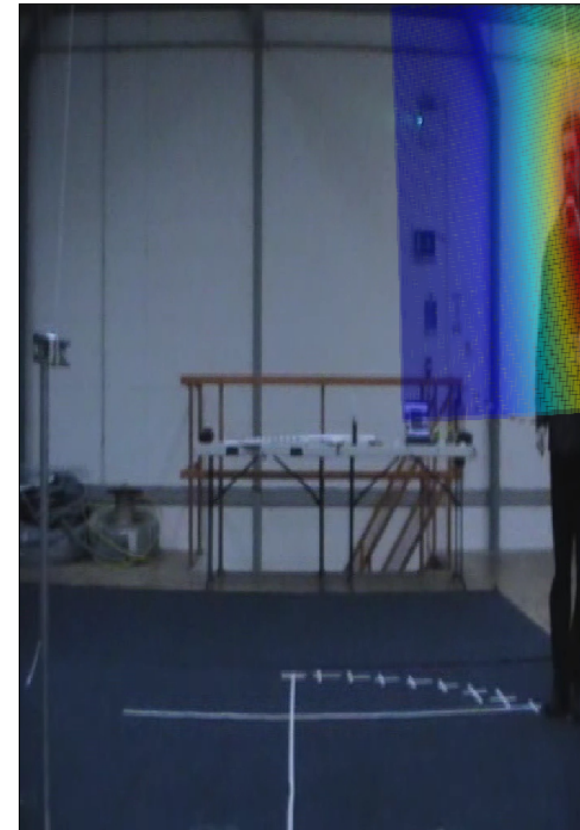
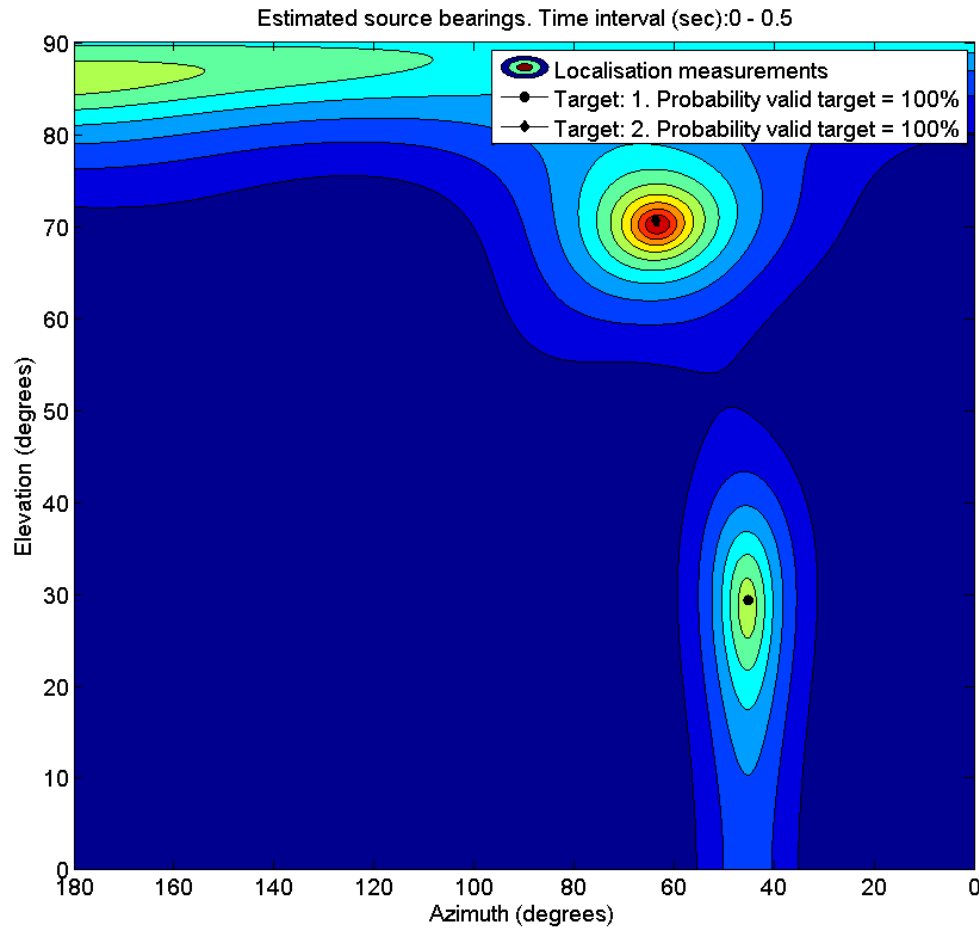




Results
Acoustic camera



A snapshot from the video output





Conclusions
and Future work



Conclusions



- iDAS can be used to develop a far field acoustic camera**
- This result requires some predictive filtering to reduce multi-path effects**
- This result can be implemented in real-time**

Next step

- Design and implementation of a massive acoustic lens**



End



Thank You



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