Underwater acoustic imaging: sparse models and implementation issues

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Underwater acoustic imaging: physically-motivated sparse models and validation on real data

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Supports:
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Outline

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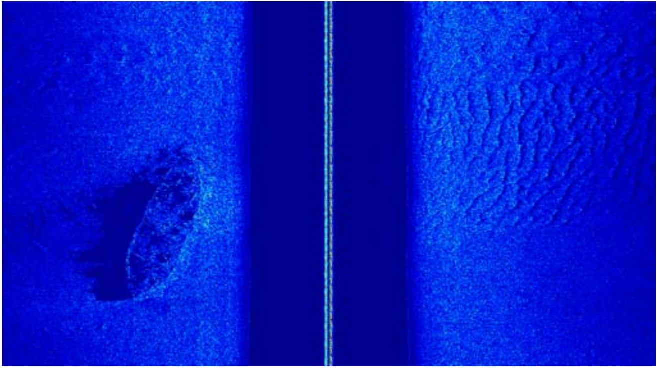
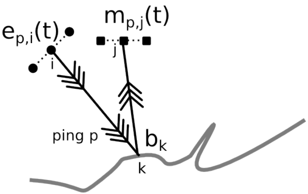
Underwater acoustic imaging (UWA)



Underwater acoustic imaging: direct problem



- Successive emission sequences, or *pings*, indexed by p.
- $\mathbf{e}_{p,i}$: emission at emitter i, ping p.
- $\mathbf{m}_{p,j}$: measurement at receiver j, ping p.
- b_k : backscattering coefficient at position k.
- $\tau_{ik} + \tau_{kj}$: propagation delay.

Direct problem:

$$\forall p, j, t,\ m_{p,j}(t) = \sum_k b_k \sum_i e_{p,i}\left(t - \tau_{ik} - \tau_{kj}\right)$$

In a matrix form,

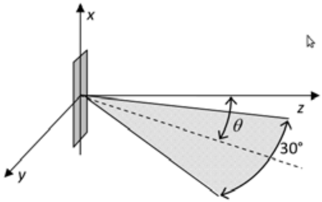
$$\mathbf{m} = \Phi \mathbf{b}$$

Underwater acoustic imaging (inverse) problem

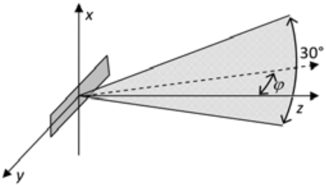
$$\mathbf{m} = \Phi \mathbf{b}$$

Goal: estimate vector $\mathbf{b}$ from measurement vector $\mathbf{m}$ and known matrix Φ (made with delayed versions of the emitted signals).

Classical approach to sonar: beamforming (BF)



Beam at emission (E(θ))



Beam at reception (R(ϕ))

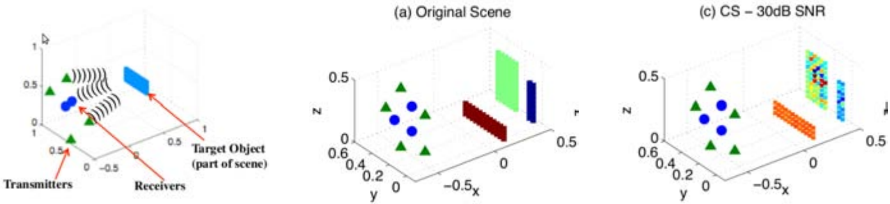
In a nutshell:

- A beam = focus on a quasi-planar region (θ or ϕ).
- Forming E or R beams = apply gains/delays to transducers.
- E(θ) beam $\cap$ R(ϕ) beam = image point in direction (θ, ϕ).
- Successive pings = successive beams with varying angles.
- BF imaging = linear estimator $\widehat{\mathbf{b}}^{\mathrm{BF}} \triangleq \mathbf{Wm}$ for some $\mathbf{W}$.

Limit.: resolution (primary lobe), artifacts (sidelobes), not 3D imaging.

Sparse approaches to sonar: state of the art

Physically-motivated sparsity: most of the points in the 3D space are not scatterers (air, water).



$$\begin{cases} \mathbf{m} = \Phi \mathbf{b} \\ \color{red}{\mathbf{b} \text{ sparse}} \end{cases} \Rightarrow \qquad \widehat{\mathbf{b}}^{CS} = \arg\min_{\mathbf{b}} \|\mathbf{b}\|_1 + \mu \|\mathbf{m} - \Phi \mathbf{b}\|_2^2$$

From:

P. Boufounos, Compressed sensing for over-the-air ultrasound, ICASSP 2011.

But: tests are on simple synthetic data.

Our focus

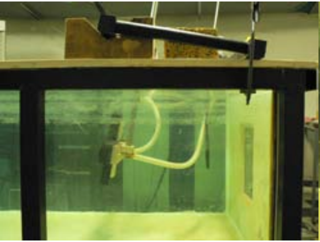
- Challenges when moving from synthetic to real data.
- New sparse model, validity of the sparse models on real data.

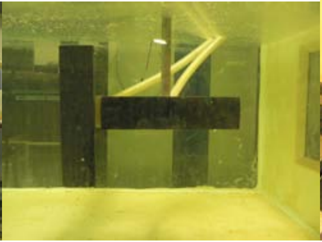
Outline

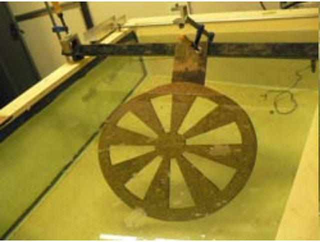
From tic to real data: challenges

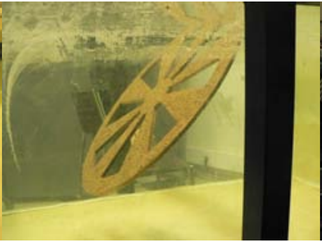
Processing real data implies:

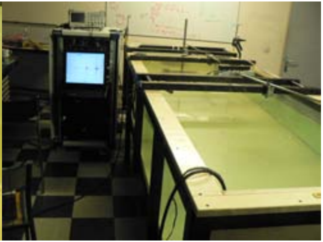
- Handling a 3D grid with a higher number of points;
- Detecting targets that are not located on the grid points;
- Detecting complex-shape objects rather than a simple pattern like a square;
- Using non-ideal transducers with directivity patterns and calibration issues;
- Handling phase issues: propagation, modulation by a carrier frequency;
- Processing noisy measurements.











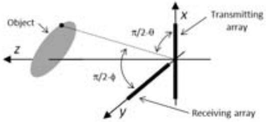
Experimental features

General settings

- 64 emission channels
- 64 reception channels
- 128 transducers (E or R each) along 2 26cm line arrays
- Carrier frequency: 480 kHz
- Bandwidth: 160 kHz
- Sampling @ 2 MHz

Current choices

- One 64-E line array
- One 64-R line array
- $\mathbf{e}_{i,p} \triangleq \delta_{i,p}\mathbf{e}$
- $\mathbf{e}$: pure sine+truncated Gauss envelope (10 periods)
- Target: ⌀52cm wheel, plywood+sand, 1m away.



Discretization & dimensionality issues

Full tank discretized with step λ: $K = 48.10^6$ voxels in the grid.
Measurement length: 13.10^6 samples.

Problem size

$$\begin{bmatrix} \\ \mathbf{m} \\ \\ \end{bmatrix} = \begin{bmatrix} & & \\ & \mathbf{\Phi} & \\ & & \end{bmatrix} \begin{bmatrix} \\ \\ \mathbf{b} \\ \\ \\ \end{bmatrix}$$

$\in \mathbb{C}^{13.10^6}$ $\quad \in \mathbb{C}^{13.10^6 \times 48.10^6}$ $\quad \in \mathbb{C}^{48.10^6}$

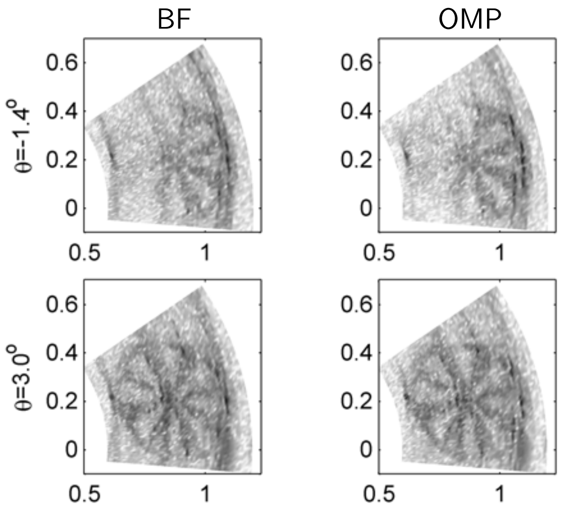
Size reduction: $\mathbf{\Phi} \in \mathbb{C}^{13.10^6 \times 48.10^6} \to \mathbf{\Phi} \in \mathbb{C}^{1,327,104 \times 70,272}$

OMP: naive $\rightarrow$ efficient implementation

OMP implementation

Residue initialization: $\mathbf{r} \leftarrow \mathbf{m}$;
Sparse support initialization: $\Omega \leftarrow \emptyset$;
for $K = 1$ to $K_{\max}$ **do**
  Atom selection: $\widehat{k} \leftarrow \arg\max_k |\langle \mathbf{a}_k, \mathbf{r} \rangle|$
    $O\left(N_T N_R N_P \times K\right) \rightarrow O\left(N_T \log N_e + N_R N_P K\right)$
  Sparse support update: $\Omega \leftarrow \Omega \cup \left\{ \widehat{k} \right\}$
  Sparse representation update: $\widehat{\mathbf{b}}_\Omega \leftarrow \Phi_\Omega^+ \mathbf{m}$ (adaptive update)
  Residue update: $\mathbf{r} \leftarrow \mathbf{m} - \Phi_\Omega \widehat{\mathbf{b}}_\Omega$
end for
Output: $\widehat{\mathbf{b}}^{\mathrm{OMP}} \leftarrow \widehat{\mathbf{b}}_\Omega$.

Results

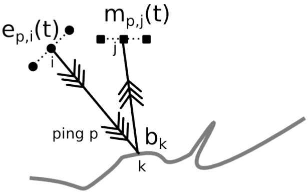


Stefanakis et al.,
Sparse Underwater Acoustic Imaging: A Case Study,
ICASSP 2012.

Outline

Directional scattering model: principle

In the standard (omnidirectional) scattering model, b_k depends on position k only:

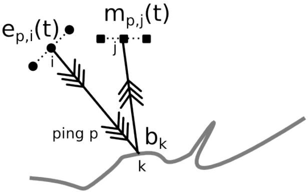


$$m_{p,j}(t) = \sum_k b_k \sum_i e_{p,i}\left(t - \tau_{ik} - \tau_{kj}\right)$$

New directional scattering model: b_{ikj} depends on the incoming direction from emitter i and outgoing direction to receiver j,

$$m_{p,j}(t) = \sum_k \sum_i b_{ikj} e_{p,i}\left(t - \tau_{ik} - \tau_{kj}\right)$$

Directional scattering model: physically-motivated

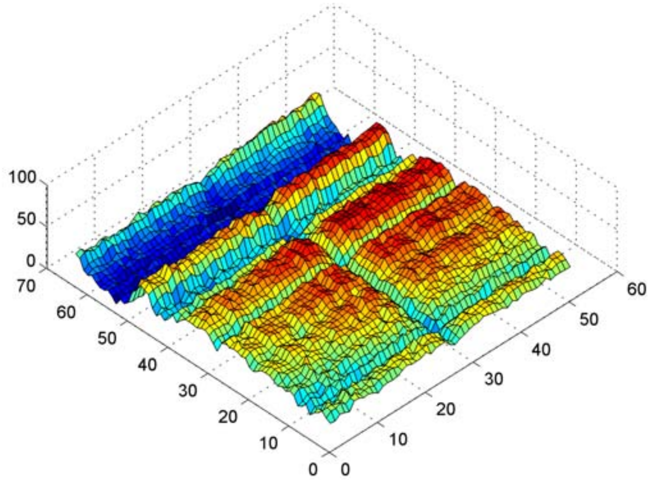


$$m_{p,j}\left(t\right) = \sum_k \sum_i {\color{red} b_{ikj}} e_{p,i}\left(t - \tau_{ik} - \tau_{kj}\right)$$

Motivations:

- scatterers are not omnidirectional
- transducers may not be calibrated: $b_{ikj} = \gamma_i b_k \gamma_j$

Directional scattering model: validation



Directional scattering model as a sparse model

$$m_{p,j}(t) = \sum_k \sum_i b_{ikj} e_{p,i}\left(t - \tau_{ik} - \tau_{kj}\right)$$

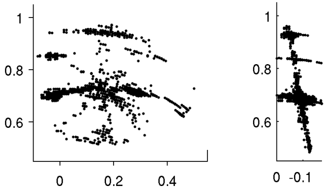
Sparsity in the omnidirectional scattering model: $\forall k \in \Omega^c, b_k = 0$
Sparsity in the directional scattering model: $\forall k \in \Omega^c, \forall i, j, b_{ikj} = 0$

The resulting model is a mixture of:

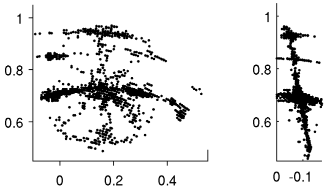
- a *joint sparse model* (Duarte et al., 2005) due to the dependance on receiver j
- a kind of *harmonic sparse model* (Gribonval and Bacry, 2003) due to the dependance on emitter i

Fresh results...

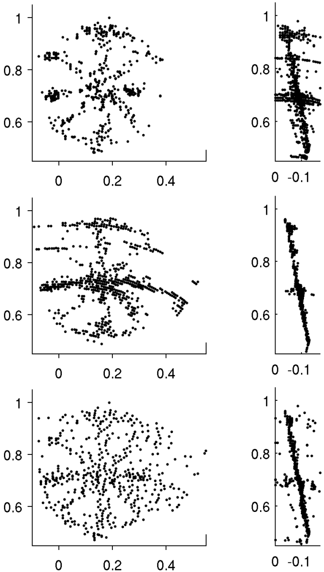
Calibrated beamforming



Calibrated omnidirectional sparse model



Variant of the directional sparse models



Outline

Conclusion

- Proposed physically-motivated sparse models
- Designed tractable algorithms
- Designed a new device
- Got new measurements
- Obtained promising results

Many perspectives

- New models: attenuation/propagation, transducer calibration, directivity
- New settings: antenna random geometry, random sequences
- Fast algorithms
- Performance assessment

Thanks!

N. Stefanakis, J. Marchal, V. Emiya, N. Bertin, R. Gribonval, P. Cervenka, *Sparse Underwater Acoustic Imaging: A Case Study*, submitted to ICASSP 2012.

New papers in preparation