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

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CIRM, Marseille, France

Supports:
ANR ASAP



Outline

Problem statement

From synthetic to real data imaging

New sparse models and model validation

Conclusion

Outline

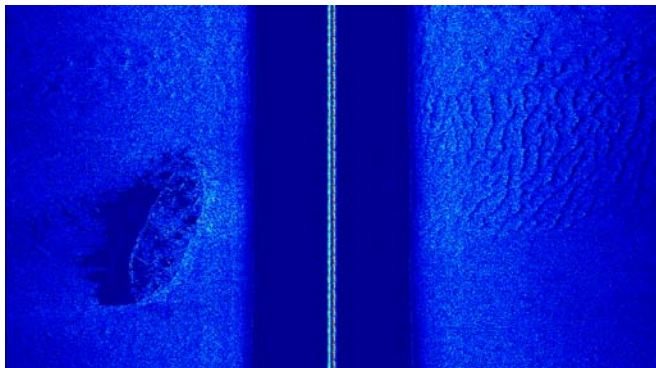
Problem statement

From synthetic to real data imaging

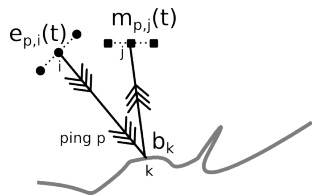
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Underwater acoustic imaging (UWA)



Underwater acoustic imaging: direct problem



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

Direct problem:

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

In a matrix form,

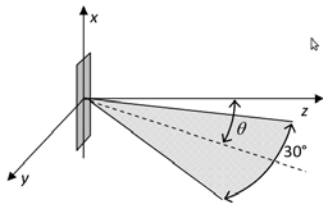
$$\mathbf{m} = \Phi \mathbf{b}$$

Underwater acoustic imaging (inverse) problem

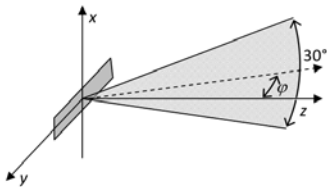
$$\mathbf{m} = \Phi \mathbf{b}$$

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 ($E(\theta)$)



Beam at reception ($R(\phi)$)

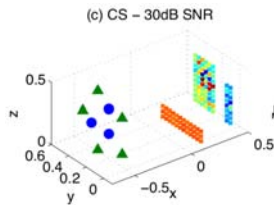
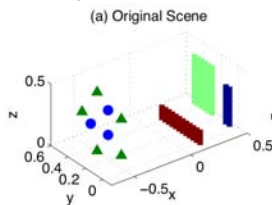
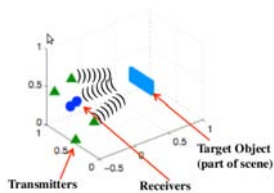
In a nutshell:

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



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

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

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From synthetic to real data imaging

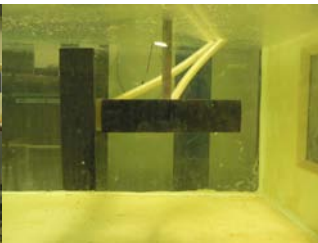
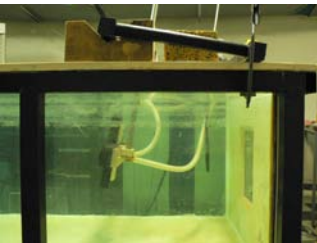
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From tic to real data: challenges

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.



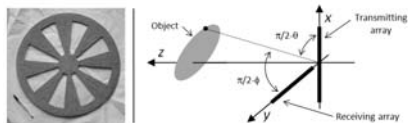
Experimental features

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: $\varnothing 52\text{cm}$ wheel, plywood+sand, 1m away.



Discretization & dimensionality issues

Full tank discretized with step λ : $K = 48 \cdot 10^6$ voxels in the grid.
Measurement length: $13 \cdot 10^6$ samples.

Problem size

$$\begin{array}{ccc} \begin{bmatrix} \mathbf{m} \end{bmatrix} & = & \begin{bmatrix} \Phi \end{bmatrix} \begin{bmatrix} \mathbf{b} \end{bmatrix} \\ \in \mathbb{C}^{13 \cdot 10^6} & & \in \mathbb{C}^{13 \cdot 10^6 \times 48 \cdot 10^6} \quad \in \mathbb{C}^{48 \cdot 10^6} \end{array}$$

Size reduction: $\Phi \in \mathbb{C}^{13 \cdot 10^6 \times 48 \cdot 10^6} \rightarrow \Phi \in \mathbb{C}^{1,327,104 \times 70,272}$

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: $\hat{k} \leftarrow \arg \max_k |\langle \mathbf{a}_k, \mathbf{r} \rangle|$

$O(N_T N_R N_P \times K) \rightarrow O(N_T \log N_e + N_R N_P K)$

Sparse support update: $\Omega \leftarrow \Omega \cup \{\hat{k}\}$

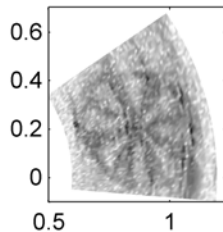
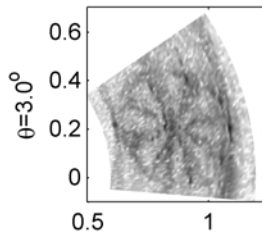
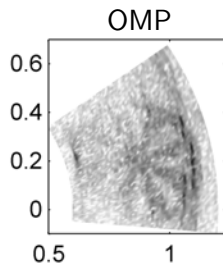
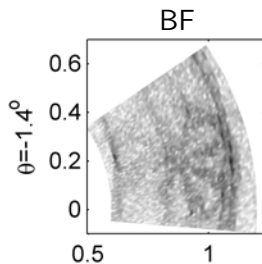
Sparse representation update: $\hat{\mathbf{b}}_{\Omega} \leftarrow \Phi_{\Omega}^+ \mathbf{m}$ (adaptive update)

Residue update: $\mathbf{r} \leftarrow \mathbf{m} - \Phi_{\Omega} \hat{\mathbf{b}}_{\Omega}$

end for

Output: $\hat{\mathbf{b}}^{\text{OMP}} \leftarrow \hat{\mathbf{b}}_{\Omega}$.

Results



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

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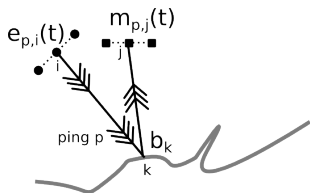
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Directional scattering model: principle

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

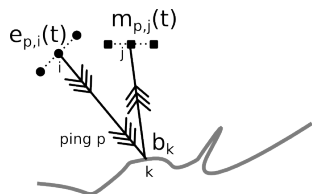


$$m_{p,j}(t) = \sum_k b_k \sum_i e_{p,i}(t - \tau_{ik} - \tau_{kj})$$

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

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

Directional scattering model: physically-motivated

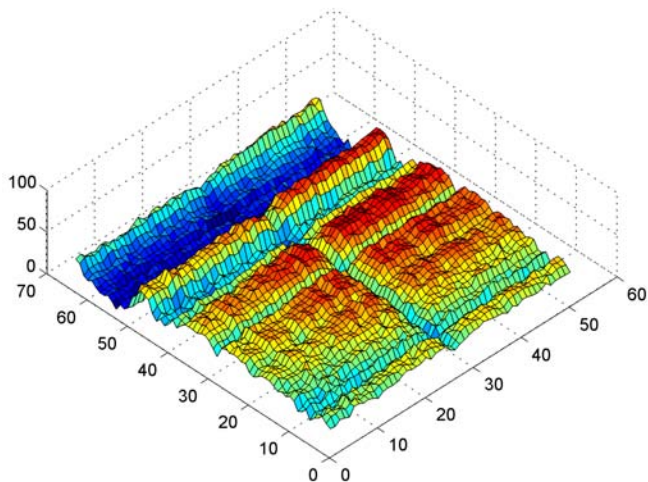


$$m_{p,j}(t) = \sum_k \sum_i b_{ikj} e_{p,i}(t - \tau_{ik} - \tau_{kj})$$

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

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

Sparsity in the omnidirectional scattering model: $\forall k \in \Omega^c, b_k = 0$

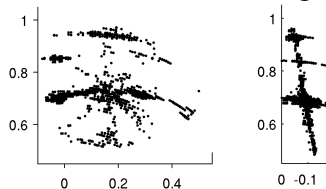
Sparsity in the directional scattering model: $\forall k \in \Omega^c, \forall i, j, b_{ikj} = 0$

The resulting model is a mixture of:

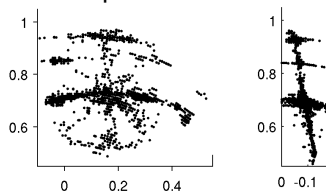
- ▶ a *joint sparse model* (Duarte et al., 2005)
due to the dependance on receiver j
- ▶ a kind of *harmonic sparse model* (Gribonval and Bacry, 2003)
due to the dependance on emitter i

Fresh results...

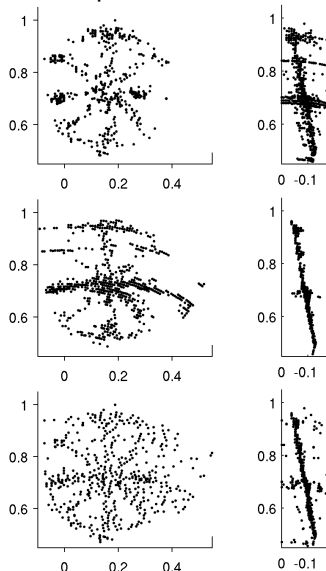
Calibrated beamforming



Calibrated omnidirectional sparse model



Variant of the directional sparse models



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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