Matched-field techniques in active and passive ocean acoustic monitoring

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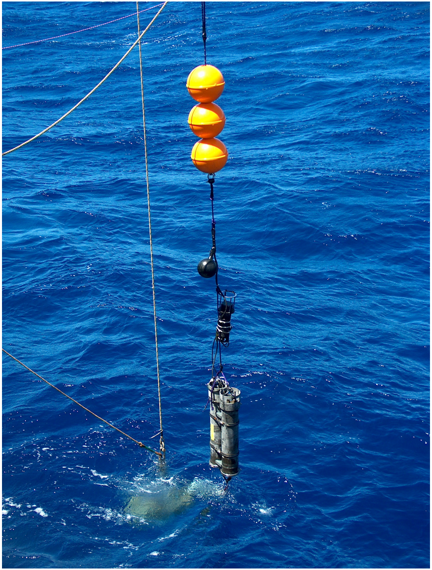
† work performed during sabbatical leave at GIPSA-Lab, Grenoble (France)

Outline



SPAWAR testbed being deployed from R/V Kilo Moana, Kauai(HI, USA), September 2005

1. processing ocean sound
2. one source - one receiver
   - the optimal receiver
   - performance criteria
   - CIMF, GMF, TRMF
   - active and passive
   - realistic examples
3. one source - many receivers
   - spatial matched-filter
   - particular cases
4. many source and receivers
5. conclusions

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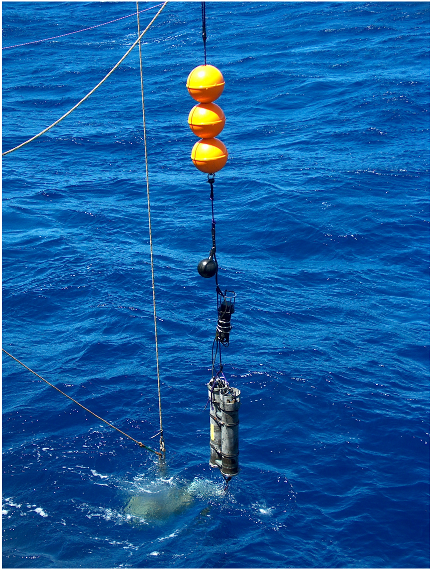

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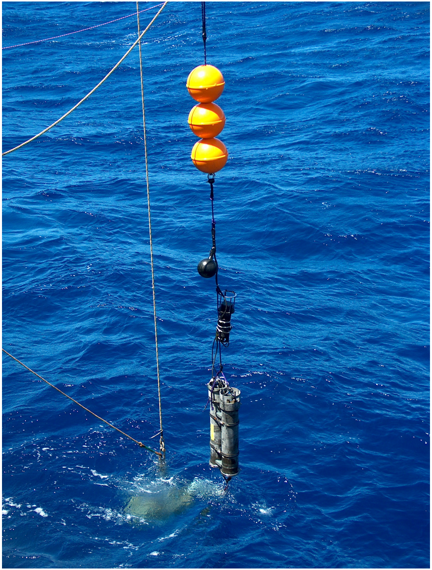

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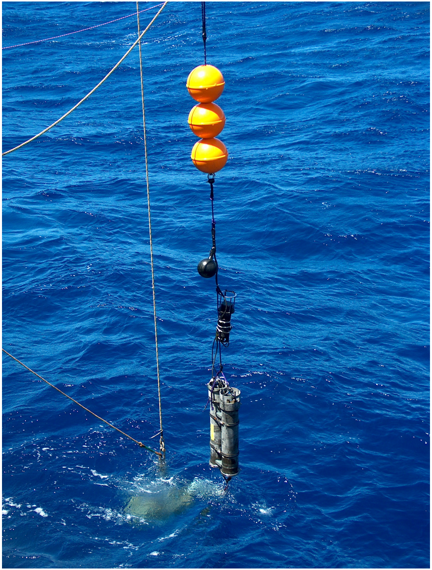

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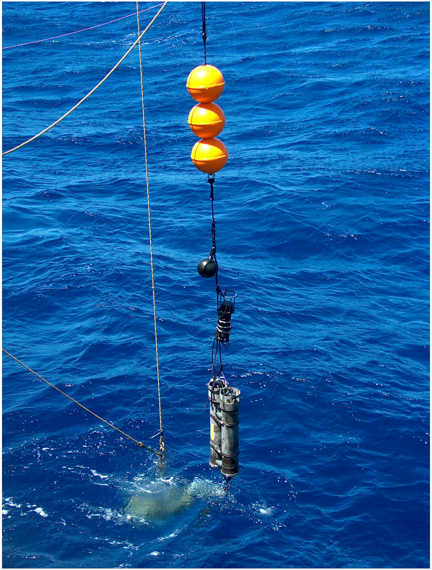

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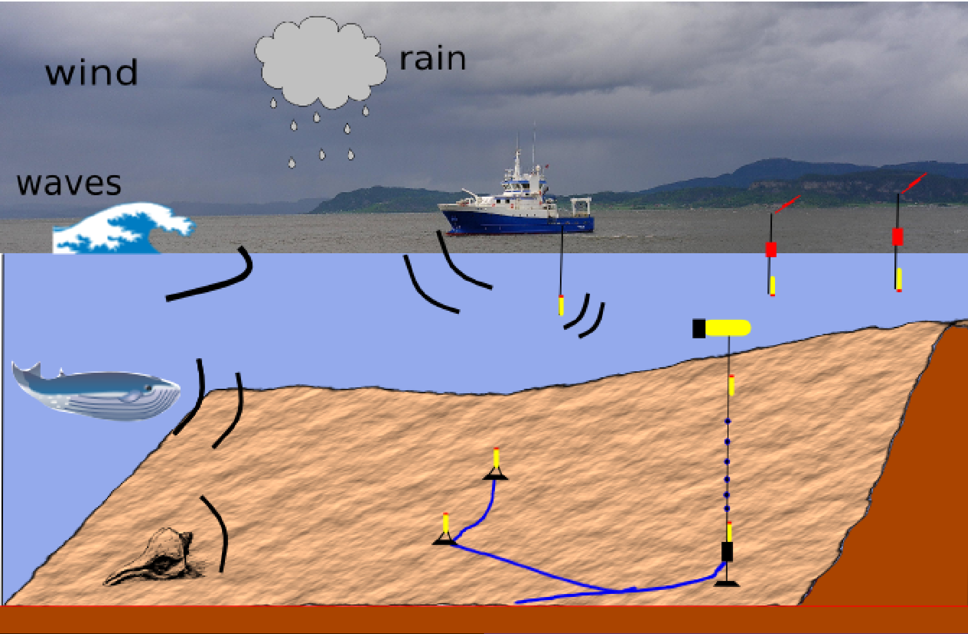
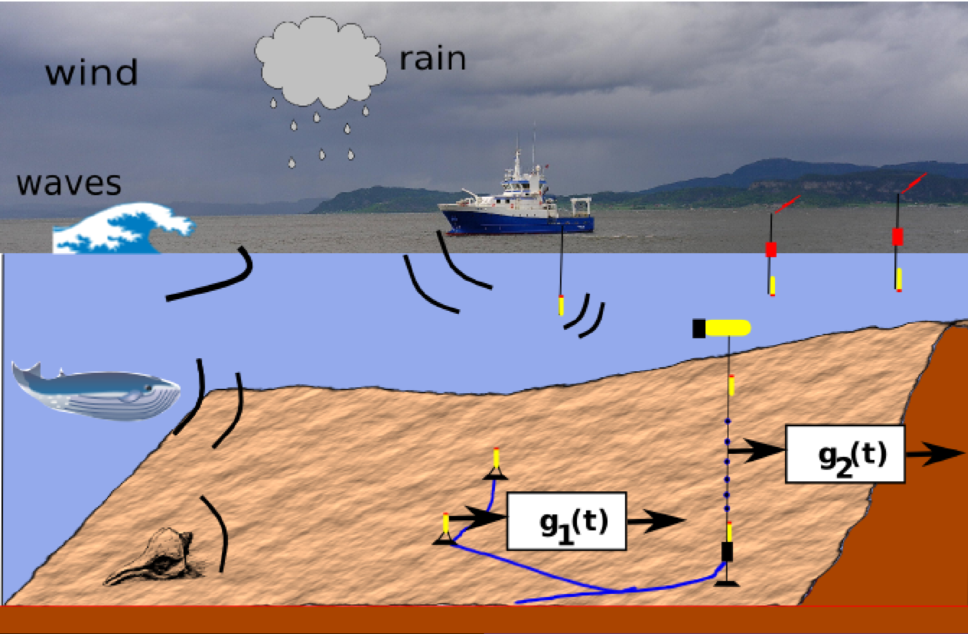
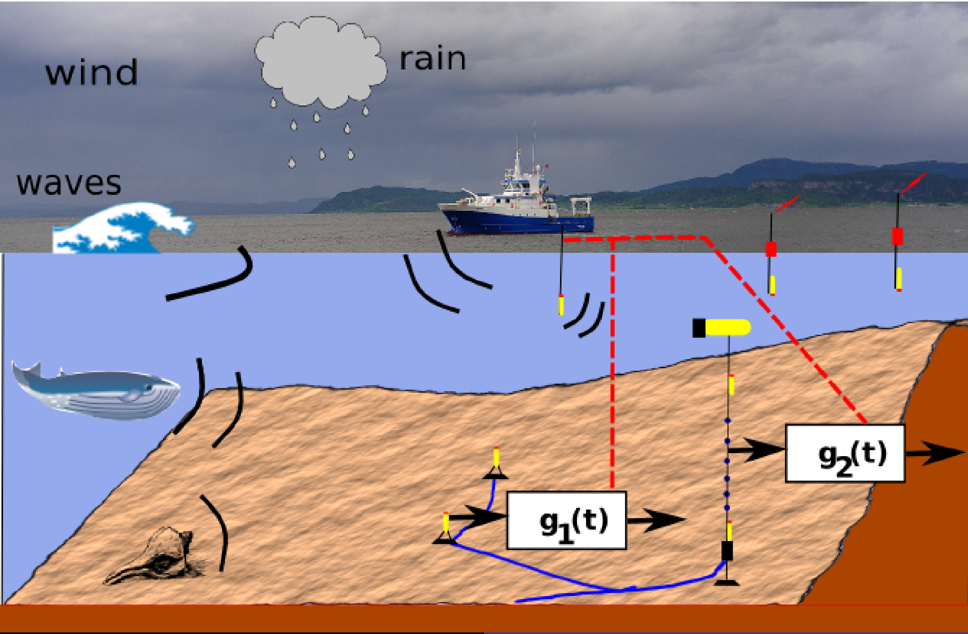
The scenario



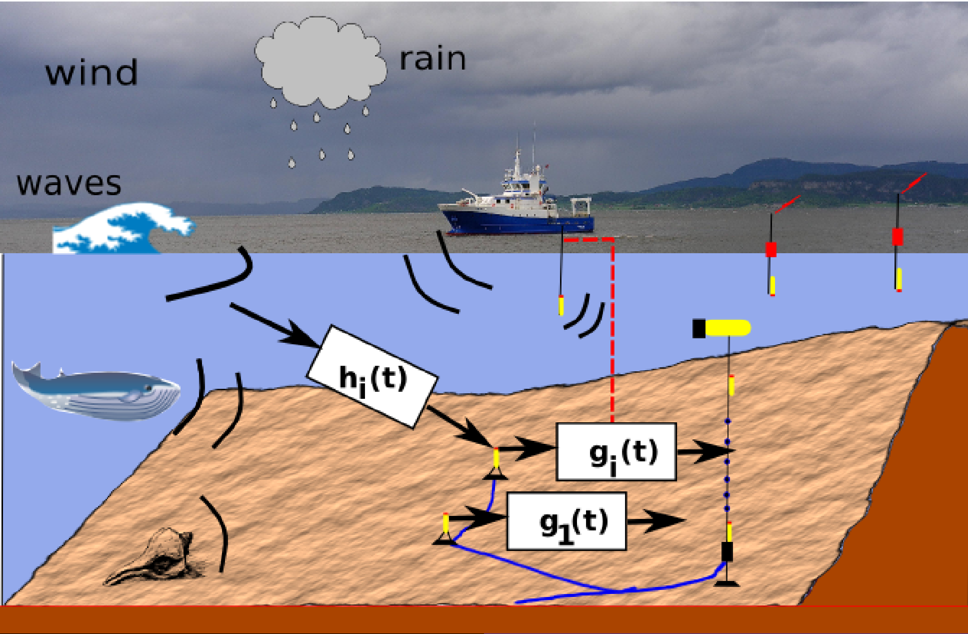
The passive case



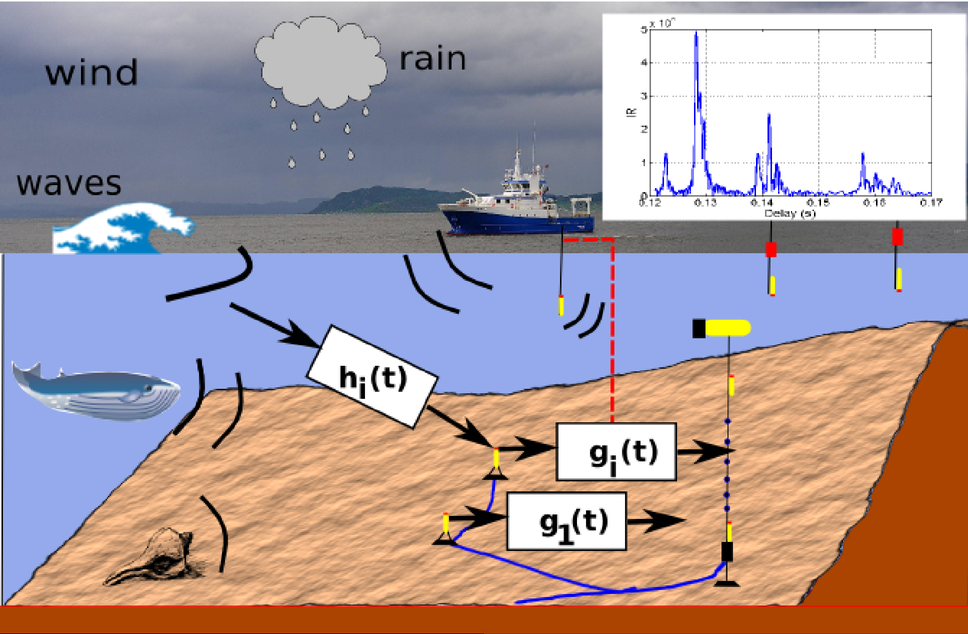
The active case



The physical model-based case



Plane-wave or full-field ?



The data model

$$\begin{aligned}\mathbf{x}(\boldsymbol{\theta}_o) &= \mathbf{H}(\boldsymbol{\theta}_o)\mathbf{s} \\ \mathbf{y}(\boldsymbol{\theta}_o) &= \mathbf{x}(\boldsymbol{\theta}_o) + \mathbf{w}(\boldsymbol{\theta}_o)\end{aligned}$$

with

$$\begin{aligned}\mathbf{x}^T &= [x(0), x(1), \ldots, x(N-1)] \\ \mathbf{H} &= \begin{bmatrix} h(0) & 0 & \ldots & 0 \\ h(1) & h(0) & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ h(N-1) & h(N-2) & \ldots & h(0) \end{bmatrix} \\ \mathbf{s}^T &= [s(0), s(1), \ldots, s(N-1)], \qquad \text{deterministic or } \mathcal{N}(\mathbf{0}, \mathbf{C}_s) \\ \mathbf{w}^T &= [w(0), w(1), \ldots, w(N-1)], \qquad \mathcal{N}(\mathbf{0}, \mathbf{C}_w)\end{aligned}$$

The CMF is given by the **NP-detector** or **max SNR** matched-filter[1]

$$\hat{\mathbf{x}}(\boldsymbol{\theta}) = \mathbf{C}_w^{-1}\hat{\mathbf{H}}(\boldsymbol{\theta})\mathbf{s}$$

$$\begin{aligned} z(n) &= \hat{\mathbf{x}}^T(\boldsymbol{\theta}_o)\mathbf{y}(\boldsymbol{\theta}_o) \\ &= \mathbf{s}^T\hat{\mathbf{H}}^T(\boldsymbol{\theta})\mathbf{C}_w^{-1}\mathbf{y}(\boldsymbol{\theta}_o) \\ &= \mathbf{s}^T\hat{\mathbf{H}}^T(\boldsymbol{\theta})\mathbf{C}_w^{-1}\mathbf{x}(\boldsymbol{\theta}_o) + \mathbf{s}^T\mathbf{H}^T(\boldsymbol{\theta}_o)\mathbf{C}_w^{-1}\mathbf{w} \\ &= x_o(n) + w_o(n) \end{aligned}$$

Signal-to-noise-ratio (SNR) at filter output

$$\rho(n) = \frac{|x_o(n)|^2}{E[|w_o(n)|^2]}$$

[1] S.M. Kay, *Fundamentals of Statistical Signal Processing: Detection Theory*, Prentice-Hall, New Jersey(USA), 1998

Filter performance and GMF

$$\rho(n) = \frac{|\mathbf{s}^T\hat{\mathbf{H}}^T(\boldsymbol{\theta})\mathbf{C}_w^{-1}\mathbf{H}(\boldsymbol{\theta}_o)\mathbf{s}|^2}{\mathbf{s}^T\hat{\mathbf{H}}^T(\boldsymbol{\theta})\mathbf{C}_w^{-1}\hat{\mathbf{H}}(\boldsymbol{\theta})\mathbf{s}}$$

Optimal case $\hat{\mathbf{H}}(\boldsymbol{\theta}) = \mathbf{H}(\boldsymbol{\theta}_o)$ and

$$\rho_{\max} = \mathbf{s}^T\mathbf{H}^T(\boldsymbol{\theta}_o)\mathbf{C}_w^{-1}\mathbf{H}(\boldsymbol{\theta}_o)\mathbf{s}$$

$$|\mathrm{R}(\boldsymbol{\theta},\boldsymbol{\theta}_o)|^2 = \frac{\rho(n)}{\rho_{\max}}$$

Generalized matched-filter (GMF), physical model-based channel, performance (for white noise)

$$|\mathrm{R}_{\mathrm{GMF}}(\boldsymbol{\theta},\boldsymbol{\theta}_o)|^2 = \frac{|\mathbf{s}^T\hat{\mathbf{H}}^T(\boldsymbol{\theta})\mathbf{H}(\boldsymbol{\theta}_o)\mathbf{s}|^2}{\mathbf{s}^T\hat{\mathbf{H}}^T(\boldsymbol{\theta})\hat{\mathbf{H}}(\boldsymbol{\theta})\mathbf{s}\mathbf{s}^T\mathbf{H}^T(\boldsymbol{\theta}_o)\mathbf{H}(\boldsymbol{\theta}_o)\mathbf{s}}$$

for optimally tuned GMF $\mathrm{R}(\boldsymbol{\theta}_o,\boldsymbol{\theta}_o) = 1$.

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Sub-optimal cases: CIMF and TRMF

Channel independent matched-filter (CIMF), no channel knowledge

$$\hat{\mathbf{x}}(\boldsymbol{\theta}) = \mathbf{C}_w^{-1}\mathbf{s}$$

and performance (for white noise)

$$|\mathrm{R}_{\mathrm{CIMF}}(\boldsymbol{\theta}, \boldsymbol{\theta}_o)|^2 = \frac{|\mathbf{s}^T\mathbf{H}(\boldsymbol{\theta}_o)\mathbf{s}|^2}{\sigma_s^2\mathbf{s}^T\mathbf{H}^T(\boldsymbol{\theta}_o)\mathbf{H}(\boldsymbol{\theta}_o)\mathbf{s}}$$

Data-based/time-reversal matched-filter (TRMF), $\boldsymbol{\theta}'$ at time t',

$$\hat{\mathbf{x}}(\boldsymbol{\theta}') = \mathbf{H}(\boldsymbol{\theta}')\mathbf{s} + \mathbf{w}'$$

and performance (for white noise)

$$|\mathrm{R}_{\mathrm{TRMF}}(\boldsymbol{\theta}', \boldsymbol{\theta}_o)|^2 = \frac{|\mathbf{s}^T\mathbf{H}^T(\boldsymbol{\theta}')\mathbf{H}(\boldsymbol{\theta}_o)\mathbf{s}|^2}{\mathbf{s}^T[\mathbf{H}^T(\boldsymbol{\theta}')\mathbf{H}(\boldsymbol{\theta}') + \mathbf{H}^T(\boldsymbol{\theta}_o)\mathbf{H}(\boldsymbol{\theta}_o)]\mathbf{s}\mathbf{s}^T\mathbf{H}^T(\boldsymbol{\theta}_o)\mathbf{H}(\boldsymbol{\theta}_o)\mathbf{s}}$$

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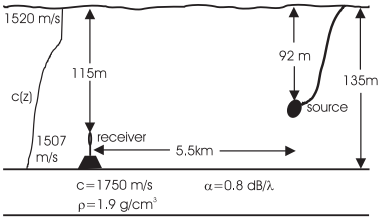
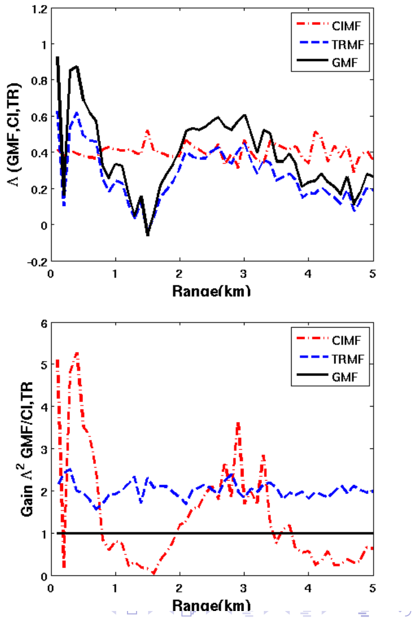
A simulation example: active case (1)

INTIMATE'96 scenario
(off Nazaré, Portugal)

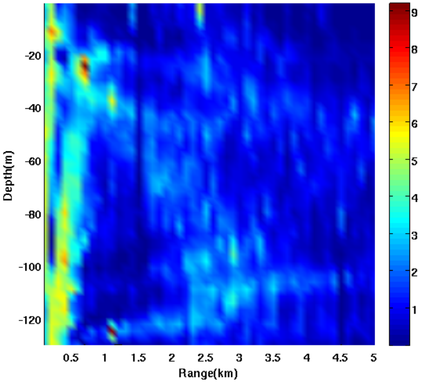


Bandwidth:
50 - 150 Hz (50 bins / Δ =2Hz)
Mismatch:
5m in water depth
Model: SNAP

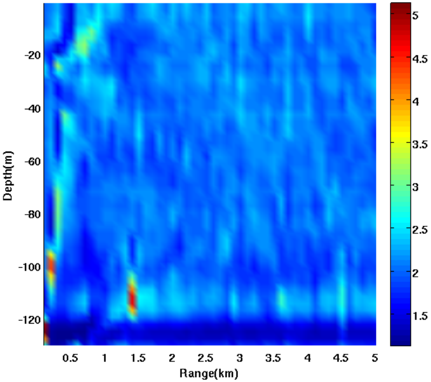


A simulation example: active case (2)

Gain GMF / CIMF

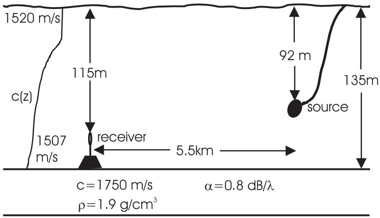


Gain GMF / TRMF

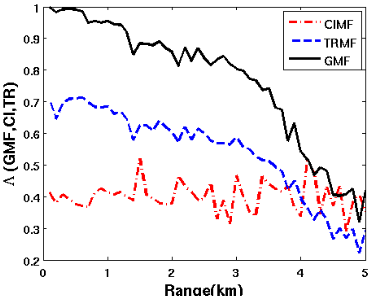


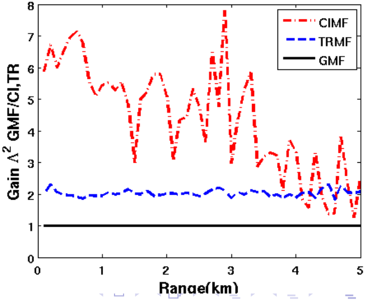
A simulation example: active case (3)

INTIMATE'96 scenario
(off Nazaré, Portugal)



Bandwidth:
50 - 150 Hz (50 bins / Δ =2Hz)
Mismatch:
C_{sed}=1700m/s, α_{sed}=1db/λ,
$\rho = 2$ Kg/cm^3
Model: SNAP





Three classes according to assumptions on emitted signal $\mathbf{s}$:

1. Possibly random: wind, waves, rainfall, shipping, some fish
2. Possibly deterministic: marine mammals and all "man-made" noise
3. Possibly either random / deterministic: ice, earthquakes, snapping shrimp and invertebrates

Address **case 1** assuming

$$\mathbf{s} : \mathcal{N}(\mathbf{0}, \mathbf{C}_s), \qquad \text{uncorrelated with noise}$$

where $\mathbf{C}_s$ may be: (1) generic, (2) uncorrelated flat $\sigma_s^2\mathbf{I}$ or (3) uncorrelated fluctuating with $\text{diag}(\sigma_{s1}^2, \sigma_{s2}^2, \ldots, \sigma_{sN}^2)$.

Wiener filter estimate-based[2]

$$\hat{\mathbf{x}}(\boldsymbol{\theta}) = \hat{\mathbf{C}}_x \hat{\mathbf{C}}_y^{-1} \mathbf{y}(\boldsymbol{\theta}_o)$$

where

$$\begin{aligned} \mathbf{C}_x &= E[\mathbf{x}\mathbf{x}^T] = \mathbf{H}\mathbf{C}_s\mathbf{H}^T \\ \mathbf{C}_y &= E[\mathbf{y}\mathbf{y}^T] = \mathbf{H}\mathbf{C}_s\mathbf{H}^T + \sigma_w^2\mathbf{I} \end{aligned}$$

and the filter output matched to the Wiener-estimate

$$z(n) = \hat{\mathbf{x}}^T(\boldsymbol{\theta})\mathbf{y}(\boldsymbol{\theta}_o)$$

which is a quadratic form on the observation $\mathbf{y}$. The output SNR is

$$\rho(n) = \frac{\mathrm{Tr}\{\hat{\mathbf{C}}_y^{-1}\hat{\mathbf{C}}_x\mathbf{H}\mathbf{C}_s\mathbf{H}^T\}}{N\sigma_w^2\,\mathrm{Tr}\{\hat{\mathbf{C}}_y^{-1}\hat{\mathbf{C}}_x\}}$$

[2] Davenport and Root, *An Introduction to the Theory of Random Signals and Noise*, IEEE Press, New York, 1987

Gaussian signal in Gaussian noise (2)

Generalized Wiener-filter (GWF)-based performance ratio

$$\mathrm{R}_{\mathrm{GWF}}(\boldsymbol{\theta}, \boldsymbol{\theta}_o) = \frac{\mathrm{Tr}\{\mathbf{C}_y^{-1}\mathbf{C}_x\}}{\mathrm{Tr}\{\hat{\mathbf{C}}_y^{-1}\hat{\mathbf{C}}_x\}} \frac{\mathrm{Tr}\{\hat{\mathbf{C}}_y^{-1}\hat{\mathbf{C}}_x\mathbf{H}\mathbf{C}_s\mathbf{H}^T\}}{\mathrm{Tr}\{\mathbf{C}_y^{-1}\mathbf{C}_x\mathbf{H}\mathbf{C}_s\mathbf{H}^T\}}.$$

In the *channel independent Wiener-filter* (CIWF)-based case

$$\hat{\mathbf{x}}(\boldsymbol{\theta}) = \mathbf{C}_s(\mathbf{C}_s + \sigma_w^2\mathbf{I})^{-1}\mathbf{y}(\boldsymbol{\theta}_o)$$

$$\mathrm{R}_{\mathrm{CIWF}}(\boldsymbol{\theta}_o) = \frac{\mathrm{Tr}\{\mathbf{C}_y^{-1}\mathbf{C}_x\}}{\mathrm{Tr}\{(\mathbf{C}_s + \sigma_w^2\mathbf{I})^{-1}\mathbf{C}_s\}} \frac{\mathrm{Tr}\{(\mathbf{C}_s + \sigma_w^2\mathbf{I})^{-1}\mathbf{C}_s\mathbf{H}\mathbf{C}_s\mathbf{H}^T\}}{\mathrm{Tr}\{\mathbf{C}_y^{-1}\mathbf{C}_x\mathbf{H}\mathbf{C}_s\mathbf{H}^T\}}.$$

Gaussian signal in Gaussian noise (3)

And in the *data-based/time-reversal Wiener-filter* case, estimates at time $t' \leq t$

$$\begin{aligned}\hat{\mathbf{C}}_y &= \frac{1}{N}\sum \mathbf{y}_n\mathbf{y}_n^T \\ \hat{\sigma}_w^2 &= \frac{1}{N}\mathbf{w}^T\mathbf{w}\end{aligned}$$

and possibly

$$\hat{\mathbf{C}}_x = \hat{\mathbf{C}}_y - \hat{\sigma}_w^2\mathbf{I}$$

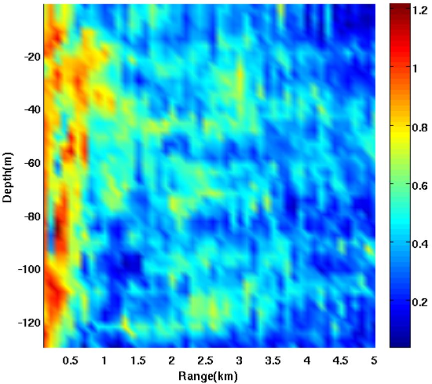
finally...

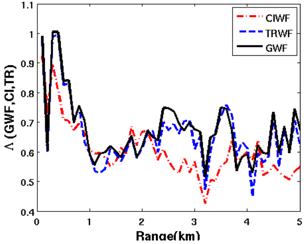
$$\mathrm{R}_{\mathrm{TRWF}}(\boldsymbol{\theta}', \boldsymbol{\theta}_o) = \frac{\mathrm{Tr}\{\mathbf{C}_y^{-1}\mathbf{C}_x\}}{\mathrm{Tr}\{\mathbf{I} - \hat{\sigma}_w^2\hat{\mathbf{C}}_y^{-1}\}}\frac{\mathrm{Tr}\{(\mathbf{I} - \hat{\sigma}_w^2\hat{\mathbf{C}}_y^{-1})\mathbf{H}\mathbf{C}_s\mathbf{H}^T\}}{\mathrm{Tr}\{\mathbf{C}_y^{-1}\mathbf{C}_x\mathbf{H}\mathbf{C}_s\mathbf{H}^T\}}.$$

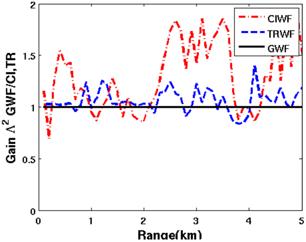
A simulation example: passive case

INTIMATE'96 scenario, N=100 snapshots, SNR = 20 dB.
Cosine-shaped fluctuating power in the band 50-150 Hz

Gain GWF / CIWF







One source - many receivers

Augmented data model

$$\begin{aligned} \mathbf{x}_a(\boldsymbol{\theta}_o) &= \mathbf{H}_a(\boldsymbol{\theta}_o)\mathbf{s} \\ \mathbf{y}_a(\boldsymbol{\theta}_o) &= \mathbf{x}_a(\boldsymbol{\theta}_o) + \mathbf{w}_a \end{aligned}$$

with

$$\begin{aligned} \text{temporal ord.} \qquad \mathbf{x}_a^T &= [\mathbf{x}^T(0), \mathbf{x}^T(2), \ldots, \mathbf{x}(N-1)^T], \\ \text{spatial ord.} \qquad \mathbf{x}_a^T &= [\mathbf{x}_1^T, \mathbf{x}_2^T, \ldots, \mathbf{x}_K^T], \end{aligned}$$

same applies to $\mathbf{y}$ and $\mathbf{w}$, and with

$$\mathbf{H}_a^T = [\mathbf{H}_1 \mathbf{H}_2 \cdots \mathbf{H}_K]$$

If observation vector is jointly Gaussian,
$\Rightarrow$ estimators are identical (notation changed accordingly).

Common particular cases (1)

Spatial combining

$$z(n) = \sum_{k=1}^{K} \hat{\mathbf{x}}_k^T(\boldsymbol{\theta})\mathbf{y}_k(\boldsymbol{\theta}_o)$$

- *planewave beamforming*: $\boldsymbol{\theta}$ is solid angle; time delays depend on array geometry; single arrival assumption; SNR gain = K.
- *spatial matched-filter*: uses channel reciprocity and linearity/superposition, to transmit $\mathbf{s} = \hat{\mathbf{H}}_k(\boldsymbol{\theta}_o)\mathbf{s}'$, pre-steered for location $\boldsymbol{\theta}_o$,

$$\mathbf{y}(\boldsymbol{\theta}) = \sum_k \mathbf{H}_k^T(\boldsymbol{\theta}_o)\hat{\mathbf{H}}_k(\boldsymbol{\theta}_o)\mathbf{s}' + \mathbf{w}$$

similar to the multiple source case, produces a peak when $\boldsymbol{\theta} = \boldsymbol{\theta}_o$. SNR gain = K.

Common particular cases (2)

- *secondary sources*: cross correlation between receivers

$$z_k(n) = \mathbf{y}_m^T(\boldsymbol{\theta}_o)\mathbf{y}_k(\boldsymbol{\theta}_o), \qquad m \neq k$$

for the estimate $\hat{\mathbf{H}}_{mk}(\theta)$, the CIR between sensors m and k.

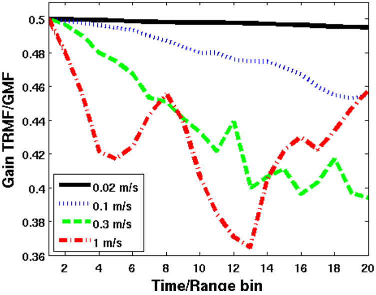
- *vector sensors*: pressure gradient composed matched-filter vector

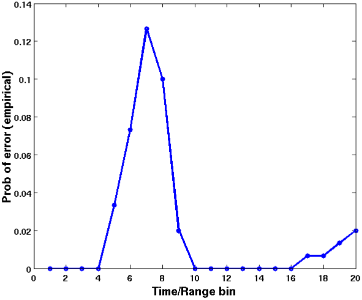
$$\hat{\mathbf{x}}_k(\boldsymbol{\theta}) = \begin{bmatrix} \mathbf{1} \\ \mathbf{u}(\boldsymbol{\theta}) \end{bmatrix} \hat{\mathbf{H}}_k(\boldsymbol{\theta})\mathbf{s}$$

with appropriate definition for $\mathbf{u}$[3]

[3] P. Santos et al. Seabed geoacoustic characterization with a vector sensor array, JASA, 128, No.5, pp.2652-2663, 2010.

Underwater communications: one to many



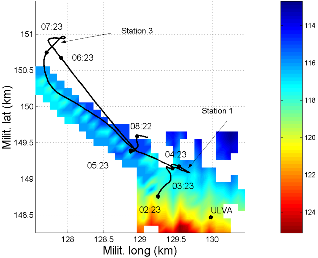


Mismatch: source range

Scenario: INT96, VLA 16 receivers

Model: SNAP

INTIFANTE'2000, Setúbal, Portugal[a]



Comms: DPSK, 1.45-1.75 kHz

Data: 20s packets, 150 bits/s

Station 4: 1.5km, depth 92m

[a] S.M.Jesus and A.J.Silva, Time reversal and spatial diversity: issues in a time varying geometry test, HFA Conf., pp.530-538, La Jolla(USA), 2004.

Multiple sources - multiple receivers

Define the modified data model

$$\begin{aligned} \mathbf{x}_a(\boldsymbol{\theta}_o) &= \mathbf{H}_A(\boldsymbol{\theta}_o)\mathbf{s}_A \\ \mathbf{y}_a(\boldsymbol{\theta}_o) &= \mathbf{x}_a(\boldsymbol{\theta}_o) + \mathbf{w}_a \end{aligned}$$

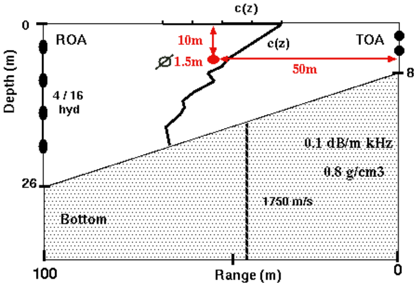
where $\mathbf{H}_A$ is now dim $KN \times LN$, N time samples, K receivers, L sources with the L-source signal vector

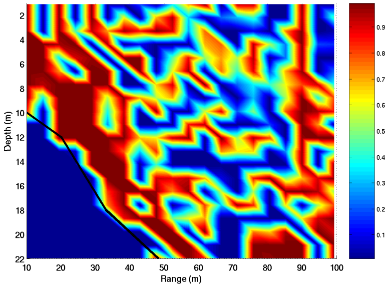
$$\mathbf{s}_A^T = [\mathbf{s}_1^T, \mathbf{s}_2^T, \ldots, \mathbf{s}_L^T].$$

No changes on the optimum receivers, but possible lth-source steering (for sensor k)

$$\hat{\mathbf{x}}_k(\boldsymbol{\theta}_l) = \hat{\mathbf{H}}_{kl}(\theta)\mathbf{s}_l$$

Underwater acoustic barriers: many to many





Scenario: UAB'07 experiment Sletvik (Norway)[a]
Mismatch: 1.5m cylinder mid water depth-range
Geometry: 4 sources, 16 receivers
Model: rays (TRACEO)
Signals: LFM 3.5 - 6.5 kHz

[a] S.M. Jesus and O. Rodríguez, A time-reversal suboptimal detector for underwater acoustic barriers, Oceans 2008, Quebec (Canada), 2008.

Conclusions

1. a common workframe for all matched-field applications
2. a tool for absolute performance and comparison
3. method characterization and sub-optimal identification
4. processing gains for *a priori* vs. non-*a priori* information methods
5. examples on realistic simulated data

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Merci

It is preferable to have an approximate answer for the right question
than the exact answer for the wrong question
A. Einstein