Compressive sensing in marine acquisition and beyond

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thanks to Xiang Li
Goals

Reduce marine acquisition costs by randomized dithering

- shorter inter shot times & continuous recording with simultaneous sources

Confront data explosion by randomized dimensionality reduction

- remove IO & PDEs-solve bottlenecks by working on small subsets of data (e.g. supershots)

Leverage recent developments in compressive sensing and message passing...
Overarching strategy

*Exploit* structure

- curvelet-domain *sparsity* of *seismic* data & images by *randomized* subsamplings that *create*
  - *incoherent* and hence *nonsparse* crosstalk/leakage, which can be removed by *transform*-domain *sparsity* promotion.
Today’s topics

Recovery of complete sequential marine data from randomized simultaneous acquisition

- compressive sensing in the field

Only dither: efficient simultaneous marine acquisition by Haneet Wason, Thursday at 13:55hrs in Room A

Acceleration of sparsity-promoting migration by message passing

- compressive sensing in the computer

Pass on the message: recent insights in large-scale sparse recovery by FJH, Wednesday at 10:55hrs in Room B
Randomized simultaneous marine acquisition
Solve an *underdetermined* system of *linear* equations:

\[
\begin{pmatrix}
\text{data} \\
\text{(measurements/observations)}
\end{pmatrix}
\xrightarrow{\text{Compressive sensing matrix:}}
\begin{pmatrix}
b \\
A
\end{pmatrix}
\xrightarrow{A = \text{RMS}^H}
\begin{pmatrix}
x_0
\end{pmatrix}
\]

- **b** ∈ \(\mathbb{C}^n\)
- **A** ∈ \(\mathbb{C}^{n \times P}\)
- **x_0** ∈ \(\mathbb{C}^P\)

where \(n \ll P\).
Sparse recovery

Sparsity-promoting program:

\[ \tilde{x} = \arg\min_x \|x\|_1 \quad \text{subject to} \quad Ax = b \]

- **support detection**
- **data-consistent amplitude recovery**

Sparsity-promoting solver: *SPG* \( \ell_1 \) \[\text{[van den Berg and Friedlander, 2008]}\]

Recover single-source prestack data volume: \( \tilde{d} = S^H \tilde{x} \)

*Randomization favors sparse recovery by rendering leakage into incoherent Gaussian noise...That’s the hope in practice...*
Random time dithering

**Acquisition Scheme**

- Supershot time (s)
- Source location

**Measurements**

- Supershot time (s)
- Receiver (#)
Recovery
[from 2X accelerated acquisition]

**Conventional processing**

Apply the adjoint of the sampling operator

+ Median filtering in the midpoint-offset domain

**Curvelet-domain sparsity-promotion**

Solve an optimization problem (e.g., one-norm minimization)
Sparsity-promoting recovery: 8.06 dB

Conventional recovery: 3.92 dB
Random time dithering
[2 source vessels]
Sparsity-promoting recovery

1 source vessel : 8.06 dB

2 source vessels : 10.3 dB
Observations

Acquisition costs reduced by randomization

- via multiple randomly dithered sources

Cost reduction at the cost of solving large-scale sparsity-promoting program

- dominated by sparsifying transform, which is $O(n \log n)$

We win because processing costs $\ll$ acquisition costs

- processing turn-around times may be an issue
Big data

“We are drowning in data but starving for understanding” USGS director Marcia McNutt

“Got data now what” Carlsson & Ghrist SIAM
Current imaging paradigm

Linear forward model:

$$A \quad x = b$$

tall matrix
(\textit{all data})
Current imaging paradigm

Imaging: \( A^H b = x_{\text{migrated}} \)

Matched filtering touches all data...
Migration results

[migration with all data]
Migration results
[true perturbation]
Costs

Computational costs dominated by \(\min(\# \text{ sources}, \# \text{ receivers})\)

- PDE solves are expensive, i.e., \(n_s n_f n_{\text{iter}} O(n^3)\)

IO dominated by \(\# \text{ sources} \times \# \text{ receivers}\)

Renders iterative methods computationally infeasible

**Solution:** Reduce \# shots & \# frequencies

- random superposition of shots (supershots)
- random selection of shots (marine)
- remove crosstalk/leakage by sparsity promotion
New paradigm

Invert underdetermined system: \( A \mathbf{x} = \mathbf{b} \)

**wide matrix**
*(randomized supershots)*

\[ n'_s n'_f \ll n_s n_f \]

with sparsity promotion.
Challenge

Reduction at the cost of solving a sparsity-promoting program

- cost dominated by (de)migrations, which are still

\[ n'_s n'_f n_{iter} O(n^3) \]

We lose because optimization requires too many iterations to obtain high-quality results

- turn-around times really become an issue
Supercooling

**Culprit:** Build up of *correlations* between the model *iterate* and *random* source *encoding* slows down *convergence*

**Solution:** *Rerandomize* by drawing *independent* supershots after each *subproblem* is solved

- *breaks correlation* buildup as in message passing
- *minimal extra cost*
- *turn each subproblem* into a *simple* “denoising” problem
Imaging results [without message passing]

3 supershots from 350 shots
10 random frequencies from 20Hz-50Hz
Imaging results
(with message passing via renewals)

3 supershots from 350 shots
10 random frequencies from 20Hz-50Hz
Migration results
[true perturbation]
Migration results

[migration with all data]
Observations

*Randomized* simultaneous marine acquisition & *sparsity-promoting* migration with *randomized* source encoding are both *instances* of *compressive sensing*

- efficient acquisition and *fast* computations
- new *paradigm* in *acquisition & inversion* where reliance on *full* sampling & touching *all* data has been *removed*
- involves *solution* of *large-scale* optimization problems, which require *fast* solution *strategies* such as message passing...
Challenges

“Data poor” acquisition:
- engineering principles for acquisition design & recovery
- calibration & sensitivity to model space errors

“Data rich” computations:
- practical workflows & recovery guarantees
- reliance on full sampling

Holy grail: integration of the two approaches...
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Further reading

Simultaneous & continuous acquisition:
– A new look at simultaneous sources by Beasley et. al., ’98.
– Changing the mindset in seismic data acquisition by Berkhout ’08.

Simultaneous simulations, imaging, and full-wave inversion:
– Phase encoding of shot records in prestack migration by Romero et. al., ’00.
– Efficient Seismic Forward Modeling using Simultaneous Random Sources and Sparsity by N. Neelamani et. al., ’08.
– Compressive simultaneous full-waveform simulation by FJH et. al., ’09.
– Randomized dimensionality reduction for full-waveform inversion by FJH & X. Li, ’10
– Fast full-wavefield seismic inversion using encoded sources by Krebs et. al., ’09
– An effective method for parameter estimation with PDE constraints with multiple right hand sides. by Eldad Haber, Matthias Chung, and Felix J. Herrmann. ’10
– Efficient least-squares imaging with sparsity promotion and compressive sensing by FJH & Li, ’12
– Fast randomized full-waveform inversion with compressive sensing by Xiang Li et. al., ’12
Further reading

**Compressive sensing & sparse solvers**
- Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information by Candes, 06.
- Compressed Sensing by D. Donoho, ’06
- Probing the Pareto frontier for basis pursuit solutions by E. van den Berg and M. Friedlander, ’08

**Message passing**
- Message passing algorithms for compressed sensing by David Donoho et. al., 2009
Thank you

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