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Multilevel Acceleration Strategy for REPSI Tim T.Y. Lin



Robust EPSI L1-minimization approach to the EPSI problem

[Lin and Herrmann, 2013 Geophysics]

While
$$\|\mathbf{p} - \mathcal{M}(\mathbf{g}_k, \mathbf{q}_k)\|_2 > \sigma$$

determine new τ_k from the $\mathbf{g}_{k+1} = \operatorname*{arg\,min}_{\mathbf{g}} \|\mathbf{p} - \mathbf{M}_{\mathbf{g}}\|_{\mathbf{q}_{k+1}}$
 $\mathbf{q}_{k+1} = \operatorname*{arg\,min}_{\mathbf{q}} \|\mathbf{p} - \mathbf{M}_{\mathbf{g}}\|_{\mathbf{q}_{k+1}}$

- from the Pareto curve
- $\mathbf{p} \mathbf{M}_{q_k} \mathbf{g} \|_2$ s.t. $\|\mathbf{g}\|_1 \leq \tau_k$
- $\mathbf{b} \mathbf{M}_{g_{k+1}} \mathbf{q} \|_2$



Robust EPSI L1-minimization approach to the EPSI problem

[Lin and Herrmann, 2013 *Geophysics*]

While
$$\|\mathbf{p} - \mathcal{M}(\mathbf{g}_k, \mathbf{q}_k)\|$$

Emits sparse, or "deconvolved" solution $\mathbf{g}_{k+1} = \arg\min\|\mathbf{p}\|$ g

 $\mathbf{q}_{k+1} = \operatorname*{arg\,min}_{\mathbf{q}} \|\mathbf{p}$

$$|_2 > \sigma$$

determine new τ_k from the Pareto curve

$$\mathbf{p} - \mathbf{M}_{q_k} \mathbf{g} \|_2$$
 s.t. $\|\mathbf{g}\|_1 \leq au_k$

$$\mathbf{b} - \mathbf{M}_{g_{k+1}} \mathbf{q} \|_2$$



L1 projection and sparsity

variable g at beginning of LASSO

$\mathbf{g}_{k+1} = \operatorname*{arg\,min}_{\mathbf{g}} \|\mathbf{p} - \mathbf{M}_{q_k} \mathbf{g}\|_2 \text{ s.t. } \|\mathbf{g}\|_1 \leq \tau_k$



L1 projection and sparsity

variable g at end of LASSO

$$\mathbf{g}_{k+1} = \operatorname*{arg\,min}_{\mathbf{g}} \|\mathbf{p} - \mathbf{M}_{q_k} \mathbf{g}\|_2 \text{ s.t. } \|\mathbf{g}\|_1 \le \tau_k$$

Emits "deconvolved" solution





Data modeled with Ricker 30Hz





Lowpassed Data

modeled with Ricker 30Hz lowpass at 40Hz (25-order, zero-phase, Hann window)





Reference REPSI primary IR from original data







REPSI primary IR from low-passed data @ 40Hz







Zero–offset trace, 1140m



Lowpass data permits coarser sampling w/o aliasing





2x decimated lowpass 30Hz

4x decimated lowpass 15Hz





Lowpass data permits coarser sampling w/o aliasing

Impulse response solutions





Lowpass data permits coarser sampling w/o aliasing





Lowpass data permits coarser sampling w/o aliasing (much faster!)

40 min



6 min

1.5 min





Multilevel strategy for EPSI

warm-start fine-scale problem with coarse-scale solutions



Idea: Warm-start with coarse-scale solutions

EPSI takes **70-100 iterations** to converge (each iteration is doing 2 SRME multiple prediction), can we make it **FASTER**?

Since decimated datasets solve much faster, we interpolate its (slightly inaccurate) G for the initial estimate to full problem

Previous Q is *discarded*

Interpolation method of G not important, just can't alias. Simple constant NMO (i.e., at water velocity) + linear interpolation works fine



Original (dx = 15m)



2x decimated lowpass 30Hz

4x decimated lowpass 15Hz





Solution of full data



Solution of 4x decimated data





Solution of full data



Solution of 4x decimated data 1600m/s NMO, linear interp 2x





Solution of 2x decimated data



Solution of 4x decimated data 1600m/s NMO, linear interp 2x





Solution of 2x decimated data



Solution on 2x dec data *continuation* from 4x dec solution





Solution of full data



Solution on 2x dec data *continuation* from 4x dec solution





Solution of full data



Solution on 2x dec data > interp 2x *continuation* from 4x dec solution





Solution of full data



Solution on 2x dec data > interp 2x *continuation* from 4x thru 2x solution







Direct Primary

Solved with plain algorithm from finest scale data





Direct Primary

Solved with spatial sampling continuation dx = 60m > 30m > 15m





Predicted Surface Multiple

Solved with plain algorithm from finest scale data

Predicted Surface Multiple

Solved with spatial sampling continuation dx = 60m > 30m > 15m

Significant speedup from bootstrapping (in 2D) Per-iteration FLOPs cost (one forward/adjoint): $n = n_{rcv} = n_{src}$ $\operatorname{Cost}(n) = \mathcal{O}(2n_t n^2 \log n)$ 2 times FFT $\operatorname{Cost}\left(\frac{1}{2}n\right) = \frac{1}{4}\mathcal{O}(2n_t n^2)$ $\operatorname{Cost}\left(\frac{1}{4}n\right) = \frac{1}{16}\mathcal{O}(2n_t n_t)$

$$n_t) + \mathcal{O}(n_f n^3)$$
 computing MCG & sum in FX

$$^{2}\log n_{t}) + \frac{1}{8}\mathcal{O}(n_{f}n^{3})$$

$$n^2 \log n_t) + \frac{1}{64} \mathcal{O}(n_f n^3)$$

Significant speedup from bootstrapping (in 2D)

$$\begin{aligned} \mathsf{Cost}(n) &= \mathcal{O}(2n_t n^2 \log n_t) + \mathcal{O}(n_f n^3) \\ & \mathbf{2} \operatorname{times} \mathsf{FFT} \\ & \operatorname{computing} \mathsf{MCG} \, \mathbf{\&} \, \operatorname{sum} \operatorname{in} \mathsf{FX} \end{aligned}$$

$$\operatorname{Cost}\left(\frac{1}{2}n, \frac{1}{2}n_{f}\right) = \frac{1}{4}\mathcal{O}(2n_{t}n^{2}\log n_{t}) + \frac{1}{16}\mathcal{O}(n_{f}n^{3})$$
$$\operatorname{Cost}\left(\frac{1}{4}n, \frac{1}{4}n_{f}\right) = \frac{1}{16}\mathcal{O}(2n_{t}n^{2}\log n_{t}) + \frac{1}{128}\mathcal{O}(n_{f}n^{3})$$

Per-iteration FLOPs cost (one forward/adjoint): $n = n_{rcv} = n_{src}$

Significant speedup from bootstrapping (in 3D)

$$\begin{aligned} \mathsf{Cost}(n) &= \mathcal{O}(2n_t n^4 \log n_t) + \mathcal{O}(n_f n^6) \\ & \mathbf{2} \operatorname{times} \mathsf{FFT} \\ & \operatorname{computing} \mathsf{MCG} \, \& \, \operatorname{sum} \operatorname{in} \mathsf{FY} \end{aligned}$$

$$\operatorname{Cost}\left(\frac{1}{2}n, \frac{1}{2}n_{f}\right) = \frac{1}{16}\mathcal{O}(2n_{t}n^{4}\log n_{t}) + \frac{1}{128}\mathcal{O}(n_{f}n^{6})$$
$$\operatorname{Cost}\left(\frac{1}{4}n, \frac{1}{4}n_{f}\right) = \frac{1}{256}\mathcal{O}(2n_{t}n^{4}\log n_{t}) + \frac{1}{8192}\mathcal{O}(n_{f}n^{6})$$

Per-iteration FLOPs cost (one forward/adjoint): $n = nx_{rcv} = ny_{rcv} = nx_{src} = ny_{src}$

0

From full data

From full data

From full data

From full data

Field data example North Sea dataset

Shot gather

NMO-corrected stack

North sea data

Shot gather and stack

Streamer data (regularized to fixedspread data) 401 source and reciever 12.5 m spatial grid 4 ms time sampling

Decimated wavefields

Original (dx = 12.5m)

2x decimated lowpass 40Hz

Rcv position (km) 0.5-Time (s) 1.5-2

4x decimated lowpass 20Hz

Solution wavefield comparison

Direct Primary Solved with plain algorithm from finest scale data

Solution wavefield comparison

Direct Primary

Solved with spatial sampling continuation dx = 50m > 25m > 12.5m

Runtime breakdown (wall time)

From full data

Solution multiple comparison

Predicted Surface Multiple Solved with plain algorithm from finest scale data

Solution multiple comparison

Predicted Surface Multiple

Solved with spatial sampling continuation dx = 50m > 25m > 12.5m

NMO Stack original data

REPSI Primaries NMO Stack Solved with plain algorithm from finest scale data

REPSI Primaries NMO Stack

Solved with spatial sampling continuation dx = 50m > 25m > 12.5m

NMO Stack original data

REPSI Multiples NMO Stack Solved with plain algorithm from finest scale data

REPSI Multiples NMO Stack

Solved with spatial sampling continuation dx = 50m > 25m > 12.5m

REPSI Multiples NMO Stack

Difference: plain algorithm accelerated algorithm

Warm-start vs from zero residual graph (for full scale problem)

Warm-start vs from zero 'G' shot gathers

Acceleration strategy summary

Start REPSI with decimated data, lowpass to avoid spatial aliasing

Once "enough" progress is made, continue with fine-scale data

Significant savings in computation cost, 100x to 200x SRMP becomes more like 20x to 30x

How low can we go? Depends on the ability of sparsity-regularized inversion to resolve wavefronts under reduced bandwidth.

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team field dataset

