Bidirectional Decon

Jon Claerbout

SEP sponsor meeting
Fallen Leaf Lake
June 2011


Fu
Yang
Jon
Antoine
Elita
Yi
STANFORD

Lots of progress!

(1) inverse theory comes of age
(2) hyperbolic penalty function
(3) non-minimum phase

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(1) Inverse theory comes of age

About 20 years ago I learned the practical adjoint idea
(To fit a regression you don't need a matrix,
only code to multiply by it and its transpose.)

In principle, it's all easy now!!
(but pitfalls are legion.)

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Albert, Art, Gus, Oz

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Cecil Green had a gracious way
to describe people who were
certain they had all the answers.

"You knew you were talking to a beginner."

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I made MANY EXAMPLES in free on-line books.
John Burg teaches me 2-D PEFs.
PEFs define covariance
PEFs are preconditioners
I discover helical filters.

Lots of progress!

(1) inverse theory comes of age
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(2) Hyperbolic Penalty Function

$$t^2 = x^2 + z_0^2$$

$$C^2 = r^2 + R^2$$

$$C_i = \sqrt{r_i^2 + R^2}$$

r is residual
C(r) is penalty
R is threshold between L1 and L2
Solutions often as fast as Conjugate Gradients

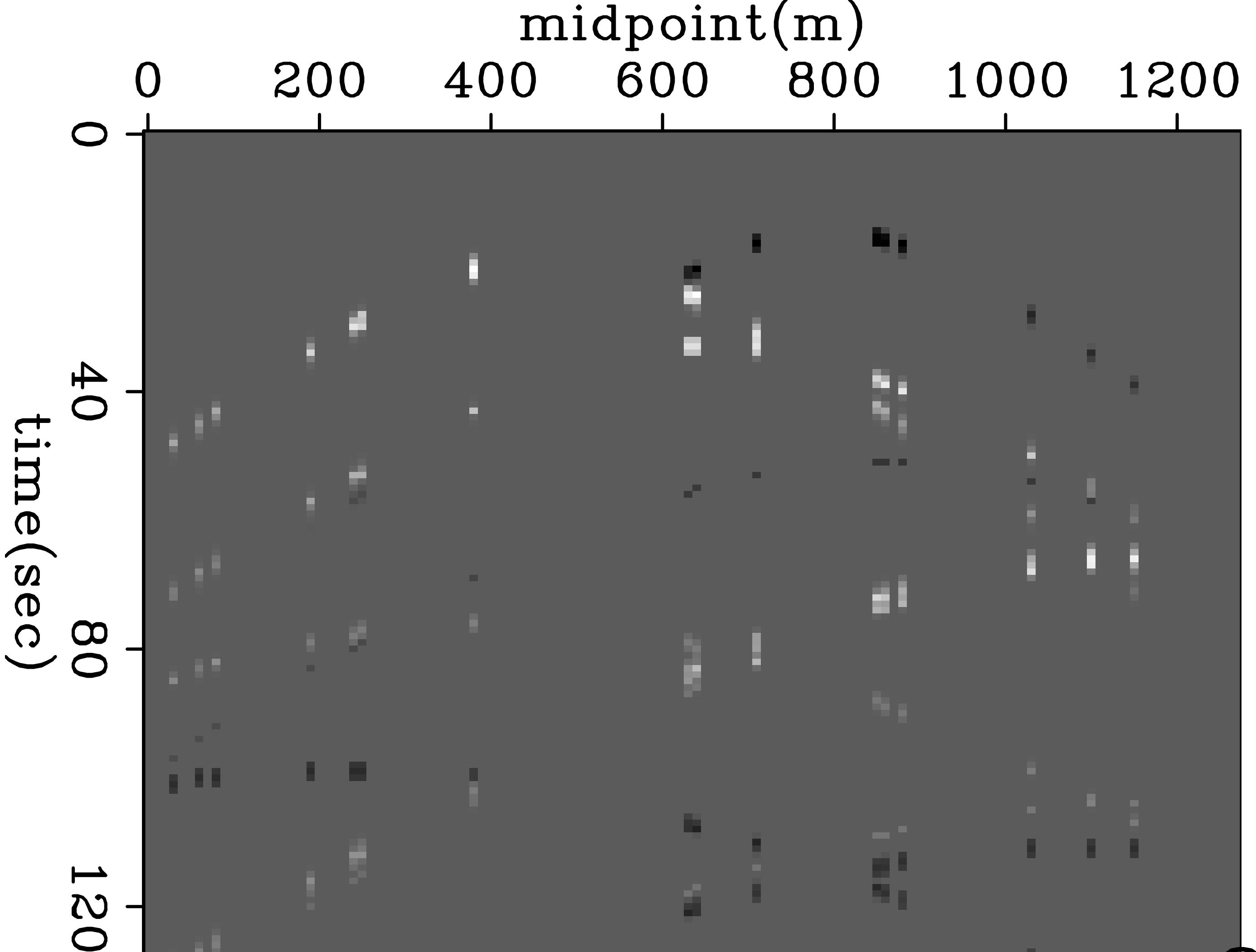
User must choose two numbers:

R_d for fitting in data space

R_m for model space regularization (blockyness)

R is the threshold parameter between L1 and L2

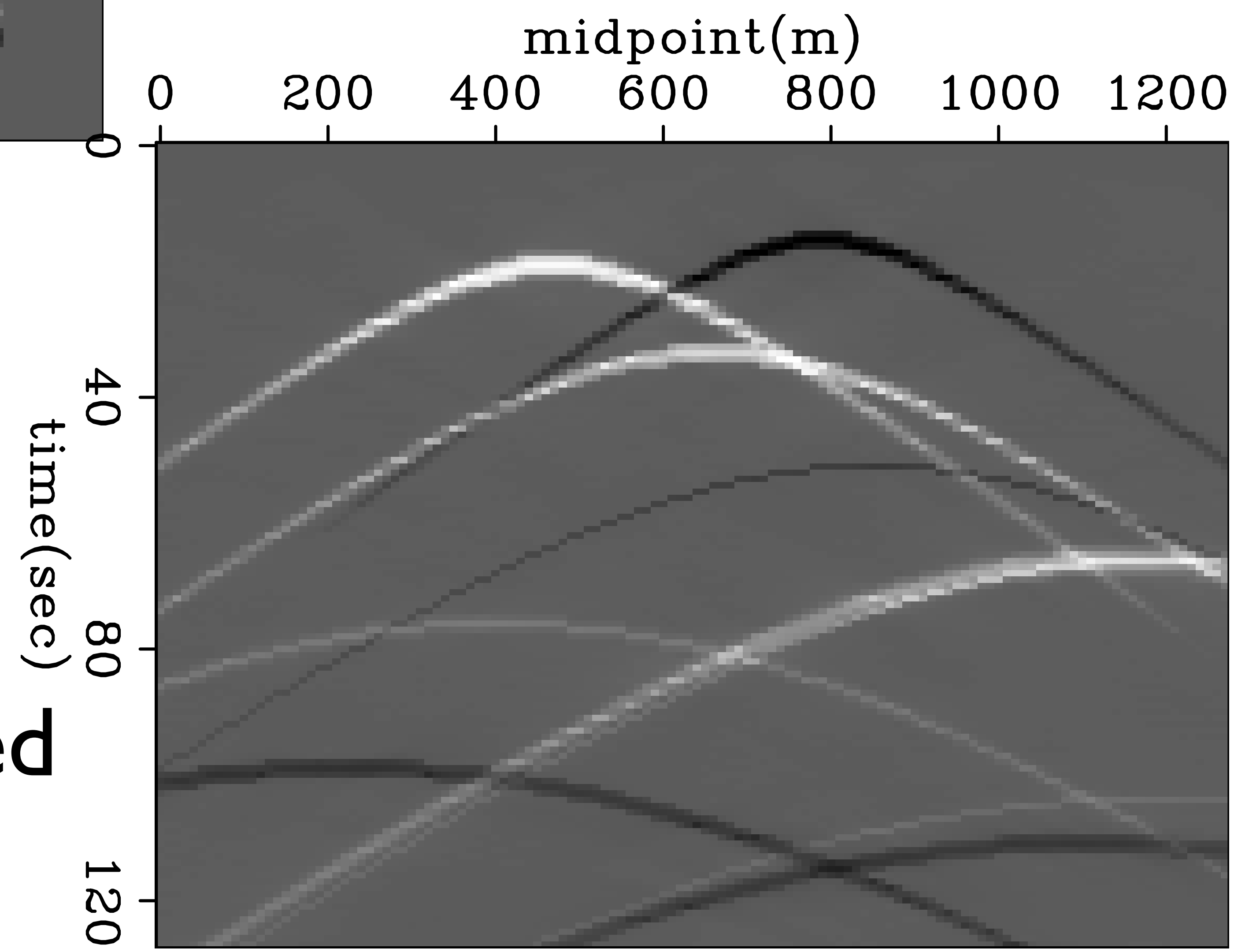
We choose thresholds using quantiles.



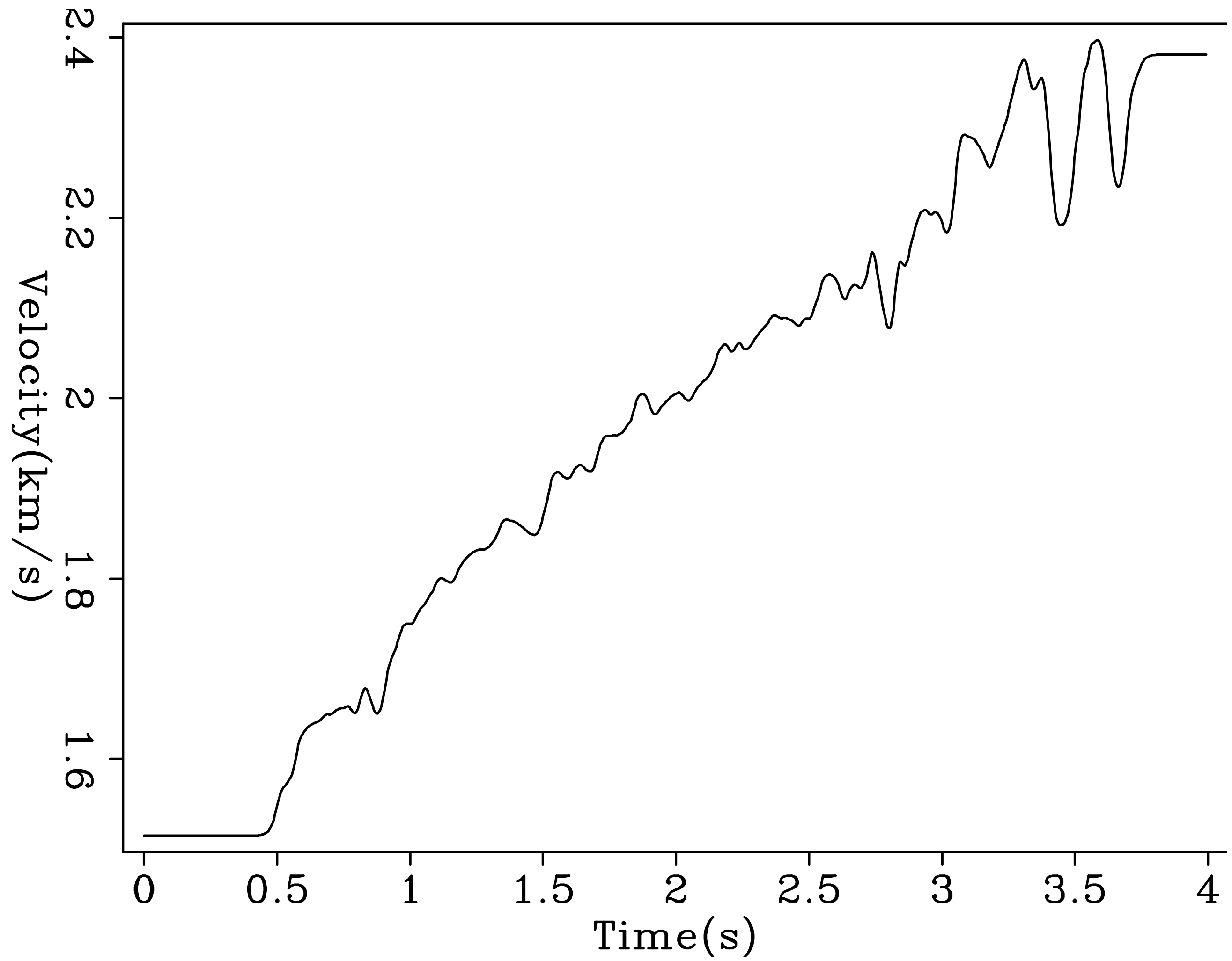
Zero-offset section, non-uniformly sampled x. Earth model with 10 point scatterers.

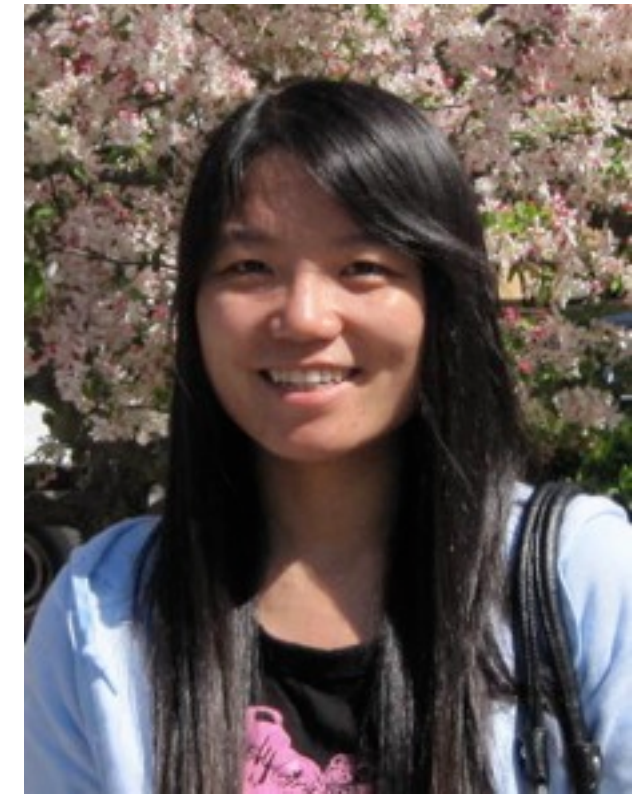
Yang Zhang

Reconstructed dense data



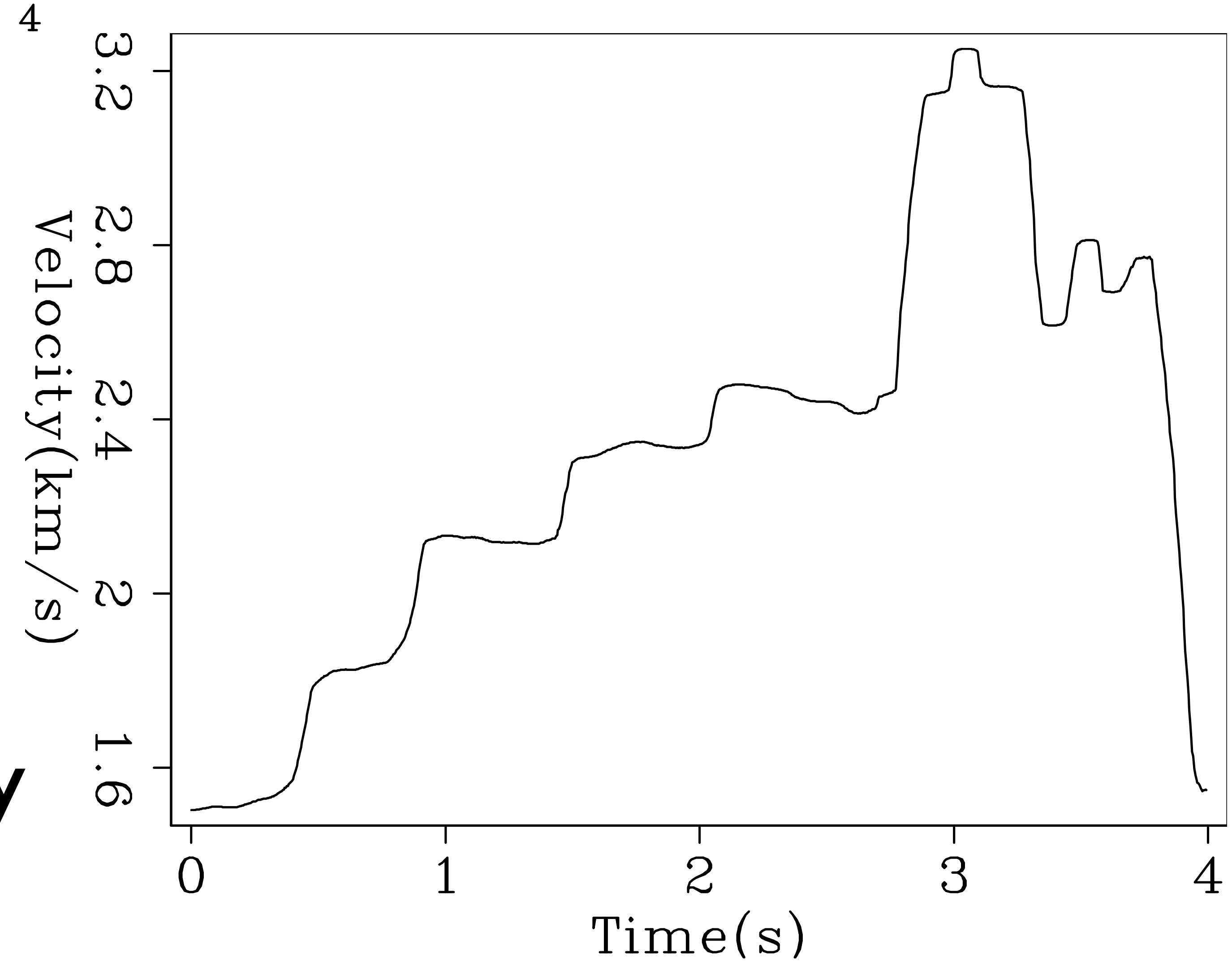
RMS velocity

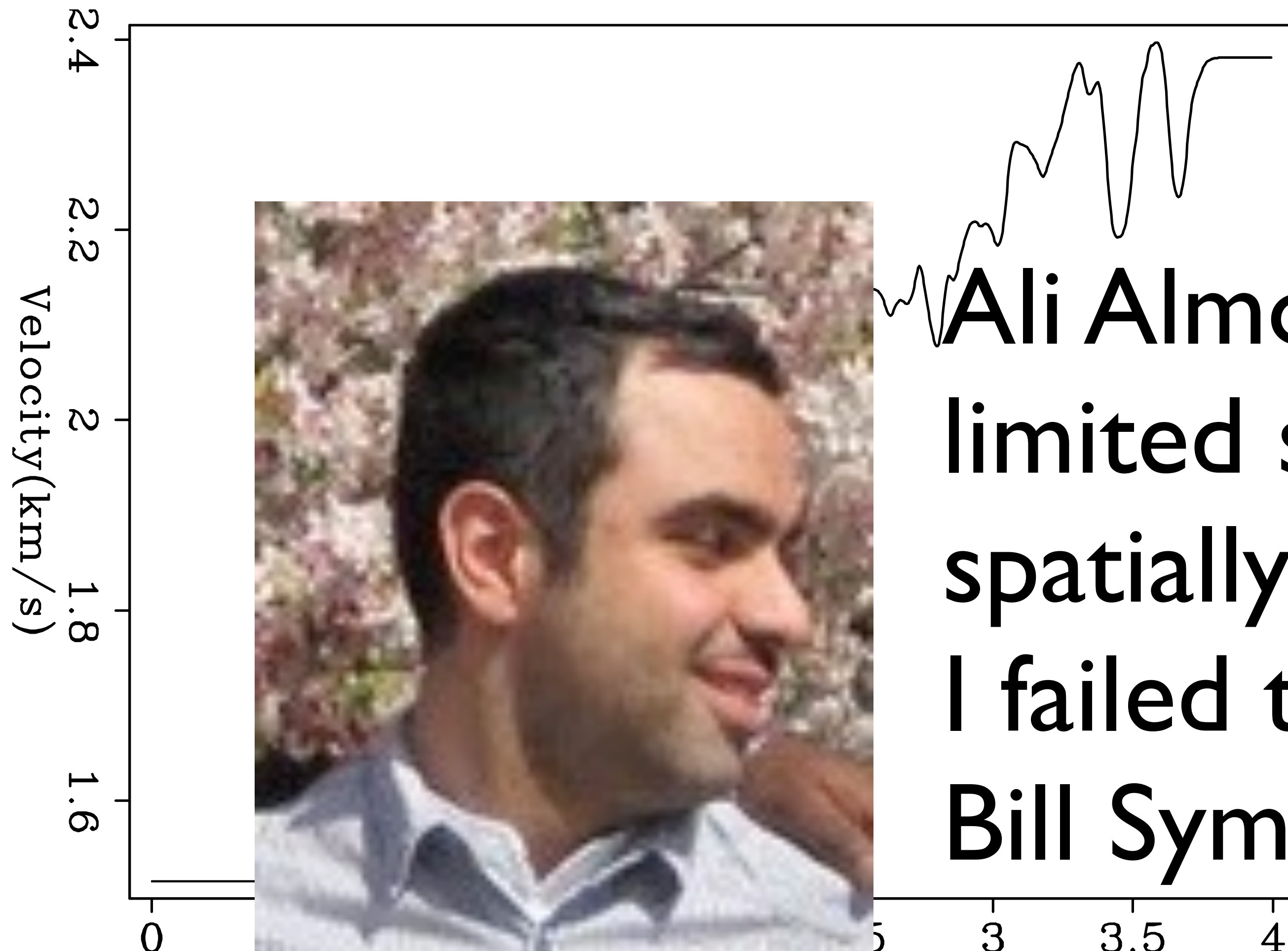




Elita (Yunyue Li)

Interval velocity

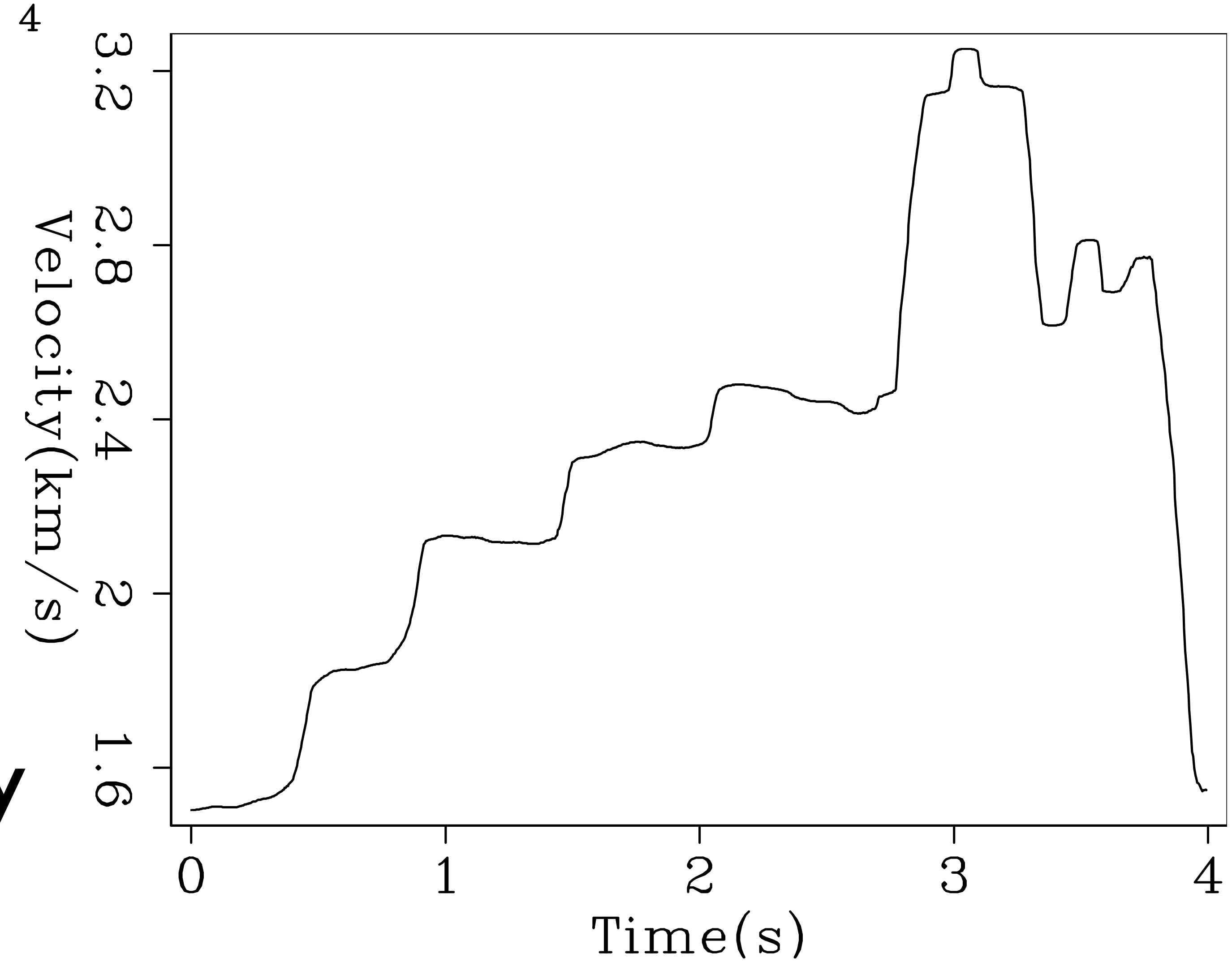




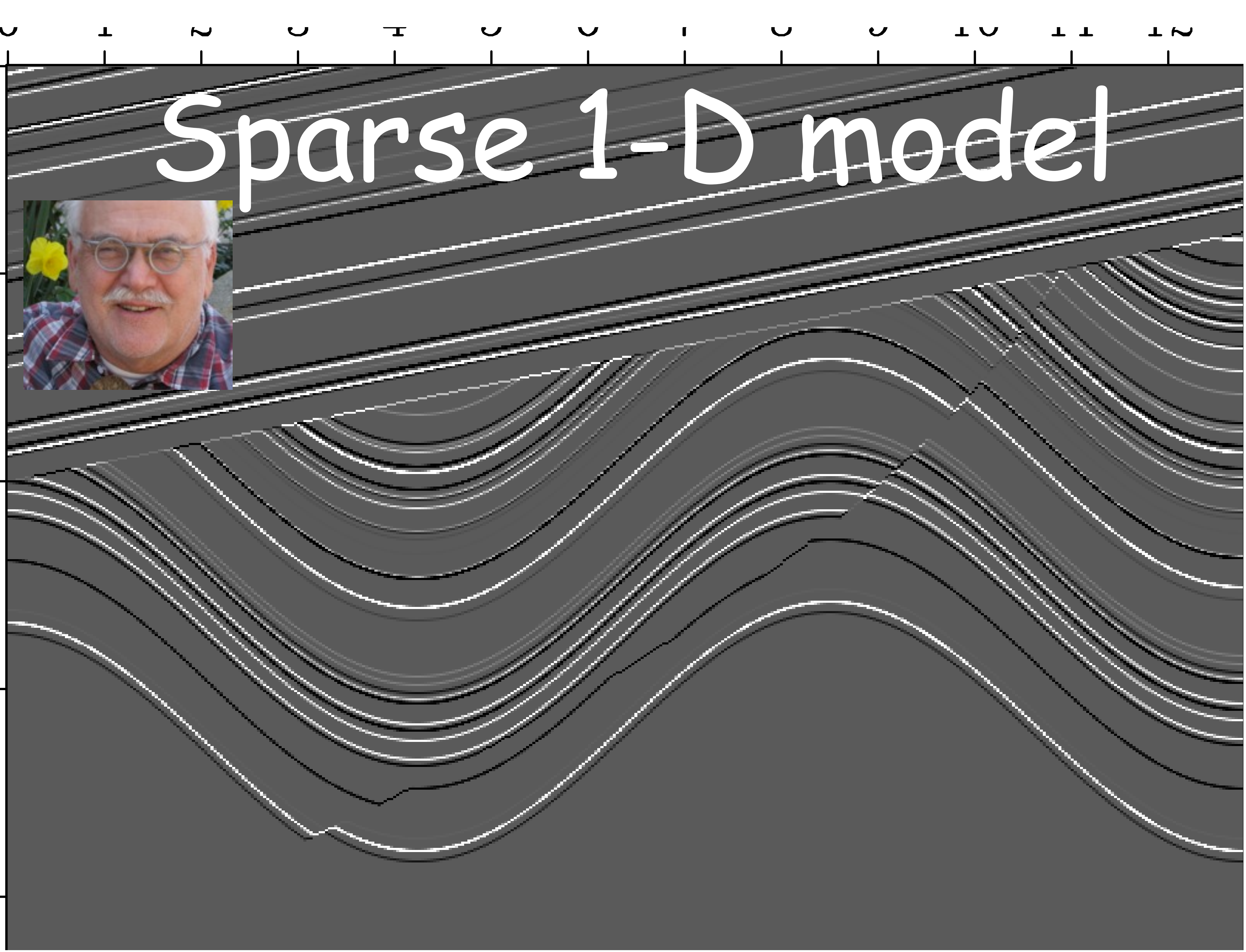
RMS velocity

Ali Almomin struggled heroically with limited success to find a good way to spatially average this technique.
I failed to figure out how to help.
Bill Symes knows how.

Interval velocity

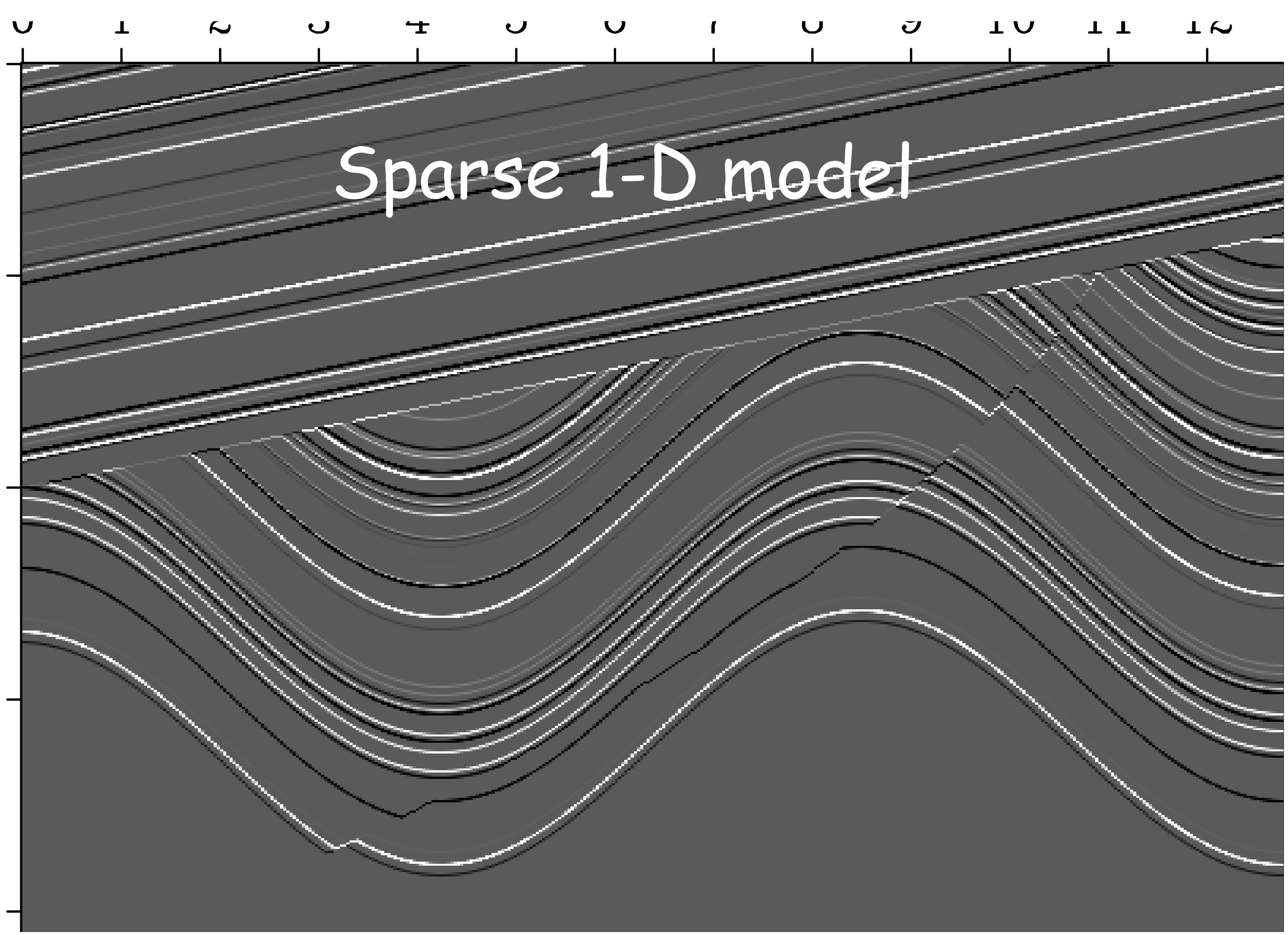


Sparse 1-D model



$$\text{wavelet} * \text{model} \rightarrow \text{Synthetic Data}$$

$$(\text{wavelet}, \text{model})? \leftarrow \text{BlindDecon}(\text{Synthetic Data})$$



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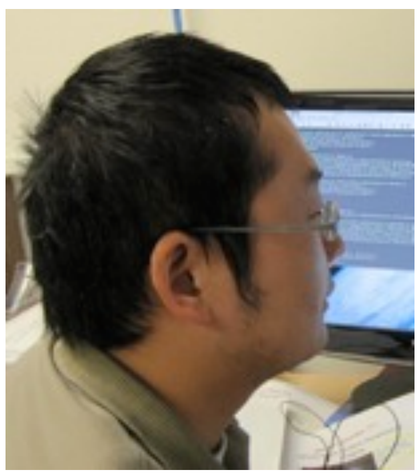
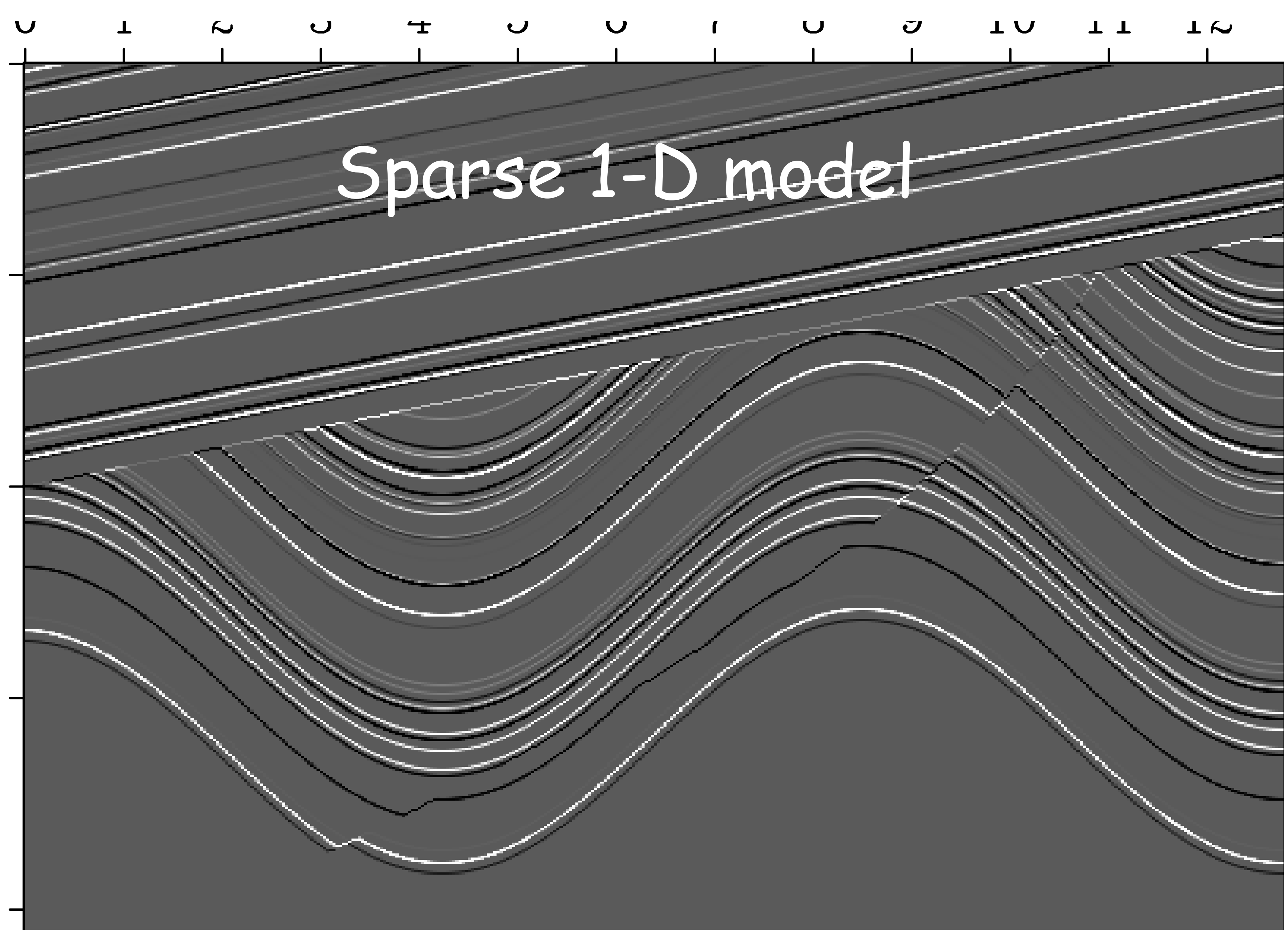
$$(\text{wavelet}, \text{model})? \leftarrow \text{BlindDecon}(\text{Synthetic Data})$$

Least squares: poor results

Hyperbolic: spectacular results!



Yang Zhang



Theory for spectacular result

$$\begin{aligned} \mathbf{Da} - \mathbf{m} \quad &=_2 \quad \mathbf{0} \\ \epsilon\ \mathbf{m} \quad &=_h \quad \mathbf{0} \end{aligned}$$

Let $\mathbf{a} = (1, a_1, a_2, a_3, \cdots) =$ unknown causal filter

Let m = unknown model (reflectivity(z))

Let D = convolution with data.

Theory for spectacular result

$$\begin{aligned} \mathbf{D}\mathbf{a} - \mathbf{m} &=_2 \mathbf{0} \\ \epsilon\, \mathbf{m} &=_h \mathbf{0} \end{aligned}$$

Let’s try it on real data!

Real data: dreadful result !

Synthetic data: spectacular result

$$\begin{aligned} \mathbf{D}\mathbf{a} - \mathbf{m} &=_2 \quad \mathbf{0} \\ \epsilon \mathbf{m} &=_h \quad \mathbf{0} \end{aligned}$$

a = unknown causal filter,

m = unknown model (reflectivity)

D = convolution with data.

Real data: **dreadful result !**

Synthetic data: spectacular result

Now what will we do?

Real data: dreadful result !

Synthetic data: spectacular result

Ali Almomin

Now what will we do?

Somebody says, “try some other data.”

Student Ali says, “Need more demanding synthetics.”

I suggest, “interaction with divergence correction,”

Student Yang says, “Try non-minimum phase wavelet.”

Real data: dreadful result !

Synthetic data: spectacular result

Ali Almomin

Now what will we do?

Somebody e other data”

Student Ali says, “ nanding synthetics.”

I suggest, “interac gence correction,”

Student Yang says, num phase wavelet.”

Bingo! Students win! Yang wins.

Non-minimum phase wavelet destroys great result.

Now what?

Tough luck, Claerbout,
the 50 year old minimum-phase assumption
is screwing you now.

The pressure is on!

Better think up a new theory! Pronto!

Lots of progress!

(1) inverse theory comes of age
(2) hyperbolic penalty function
(3) non-minimum phase

REMINDER:
minimum phase == causal inverse

An easy theory --- known to fail

$$(\cdots a_{-2}, a_{-1}, 1, a_1, a_2, \cdots)$$

(The spectrum goes haywire.)

The next slide is my pride and joy.

It reveals my new theory
that solves the problem!

It’s the only slide from this talk
you must remember!

It has 5 lines of easy definitions,
and then one line revealing the basic concept.

New theory: Bidirectional Decon

$$a = (1, a_1, a_2, a_3, \cdots) \quad \text{unknowns}$$

$$b = (1, b_1, b_2, b_3, \cdots) \quad \text{unknowns}$$

$$b^r = \text{time reverse } b$$

$$d = \text{data}$$

$$\text{reflectivity} = d * a * b^r$$

$$\text{argmin}_{\text{(a,b)}} \text{ hyp(reflectivity)}$$

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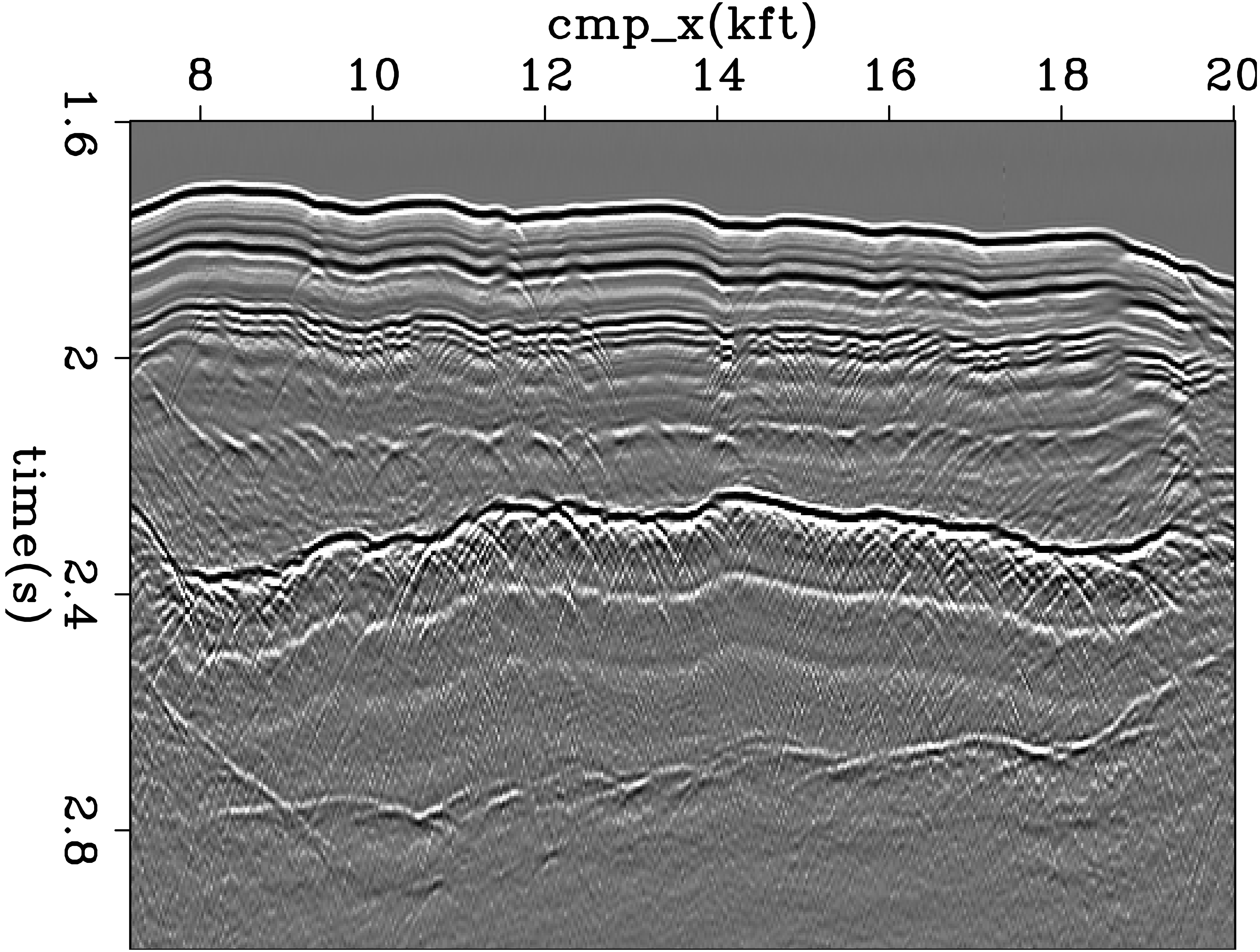
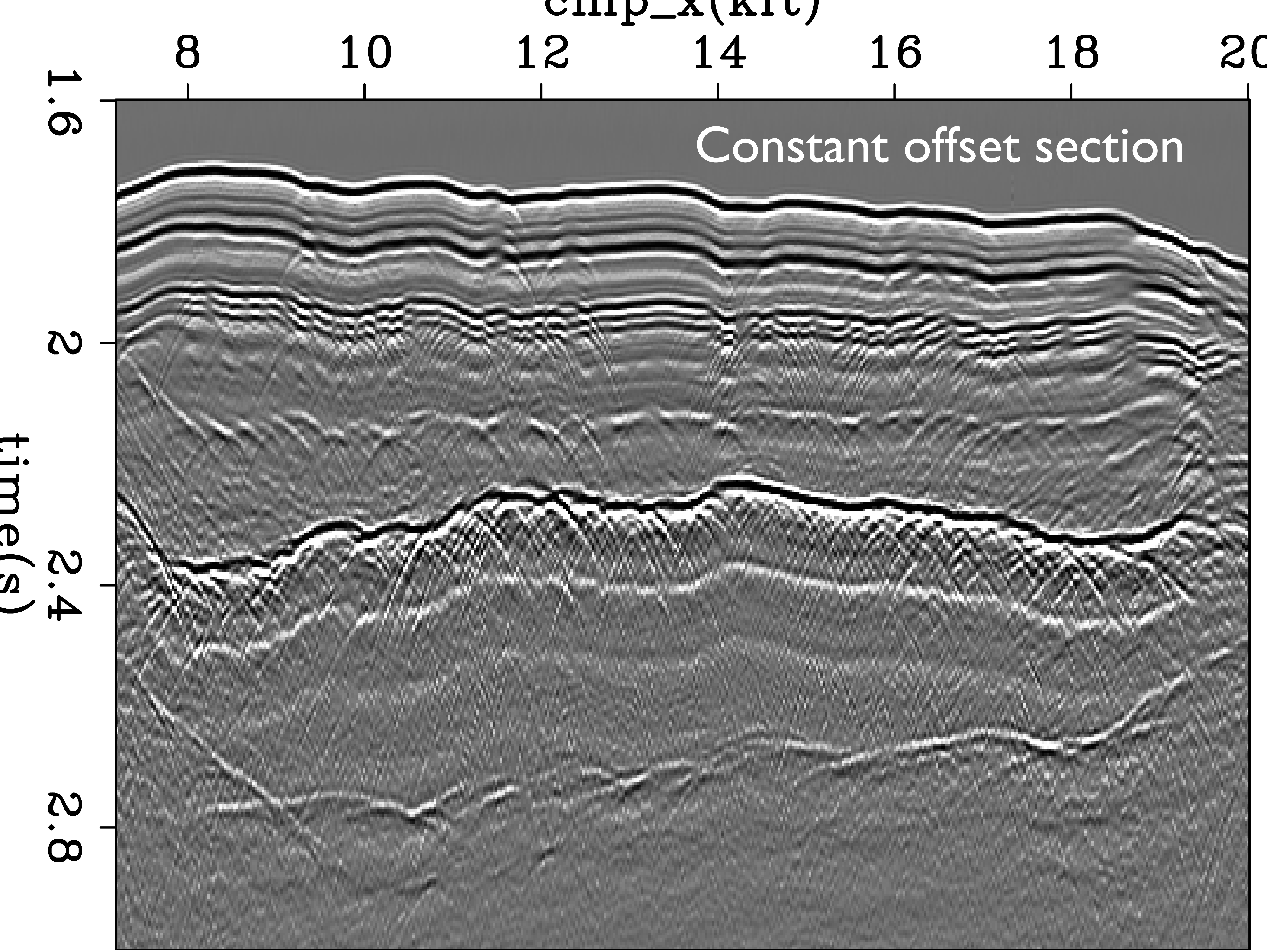
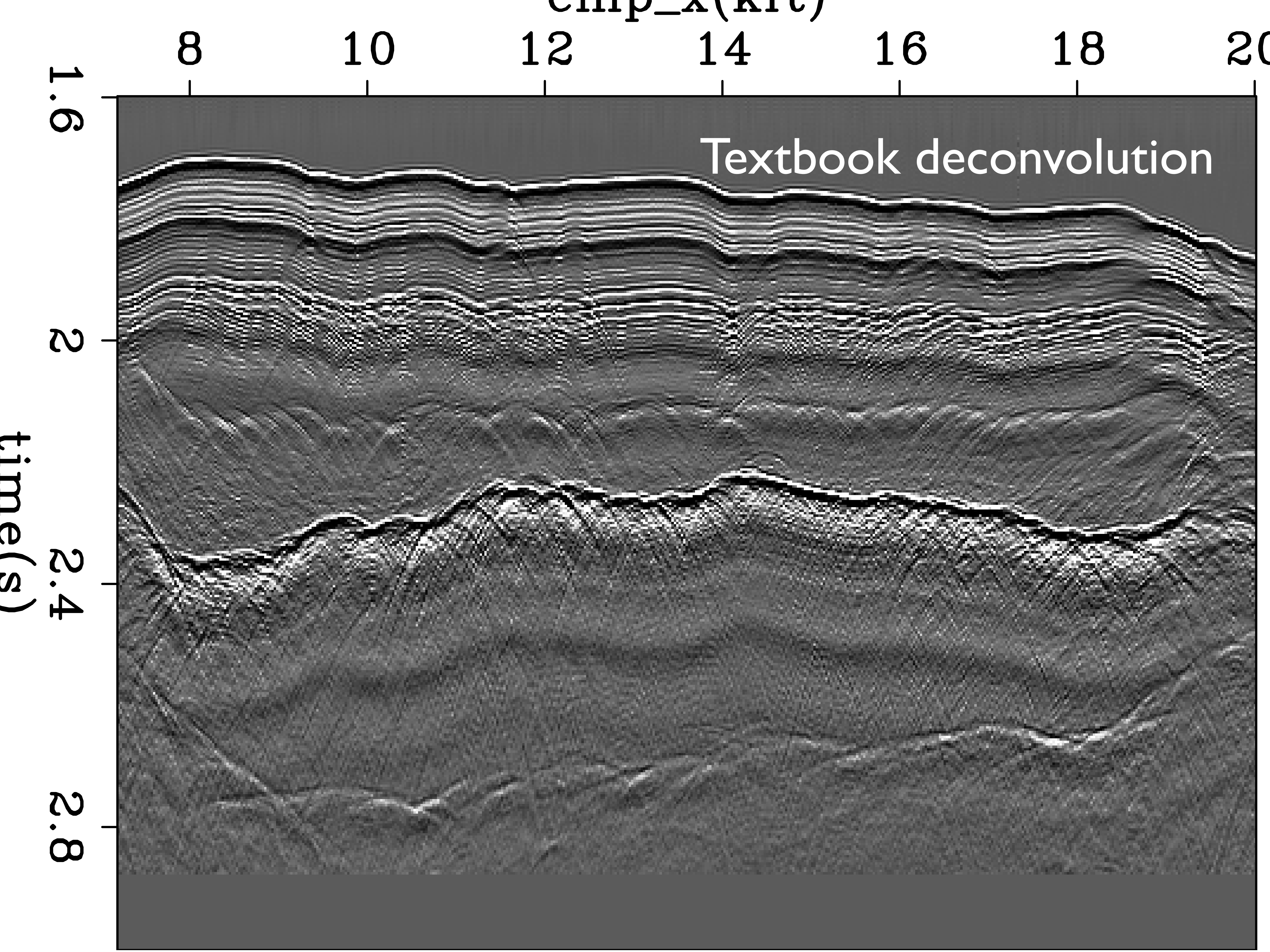
Next: View the spectacular result of Yang Zhang.

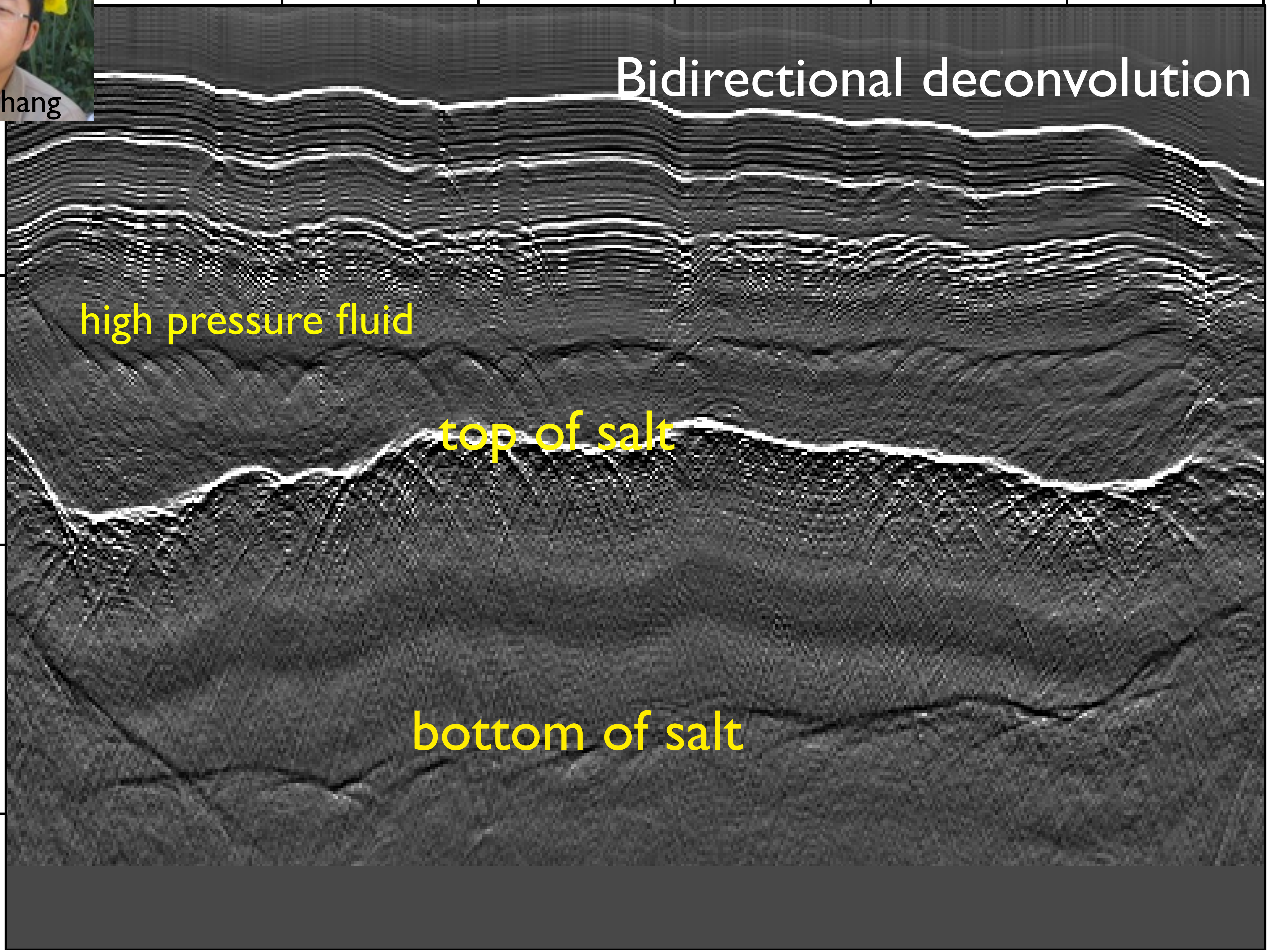
Input data is a constant offset section.




cmp_x(km)
8
10
12
14
16
18
20
1.6
2
2.4
2.8
time(s)
Constant offset section


cmp_x(km)
8
10
12
14
16
18
20
1.6
2
2.4
2.8
time(s)
Textbook deconvolution


Yang Zhang


10
12
14
16
18
2
2.4
2.8
time(s)
Bidirectional deconvolution
high pressure fluid
top of salt
bottom of salt

Ready for production?

Ready for production?

Unfortunately, not yet.

Results unstable with initial conditions,
polarity jumping around,
synthetics worse than field data!

What's happening?

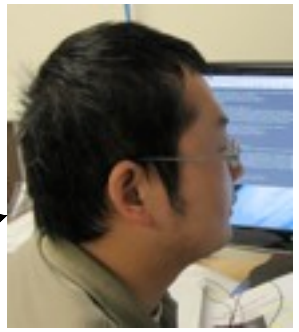
Yang Zhang leaves for imaging.

First year students arrive,
Yi Shen and Qiang Fu.

Ready for production?

Unfortunately, not yet.

Results unstable with initial conditions,
polarity jumping around,
synthetics worse than field data!



What's happening?

Yang Zhang leaves to do imaging with Biondo.

First year students arrive,
Yi Shen and Qiang Fu.

The New Team

Antoine Yi Shen Qiang Fu Jon

Where we are going,
and
why I think we will get there.

Non-linear problems demand
(1) good starting guess and
(2) cautious descent.

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My first guess starting solution was
a = PEF
b = delta function

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Experience showed b was as big as a!

b as big as a!

So, our first guess should be more symmetrical, like an inverse Ricker wavelet.

Predictive decon spikes on the <u>small first lobe</u>.

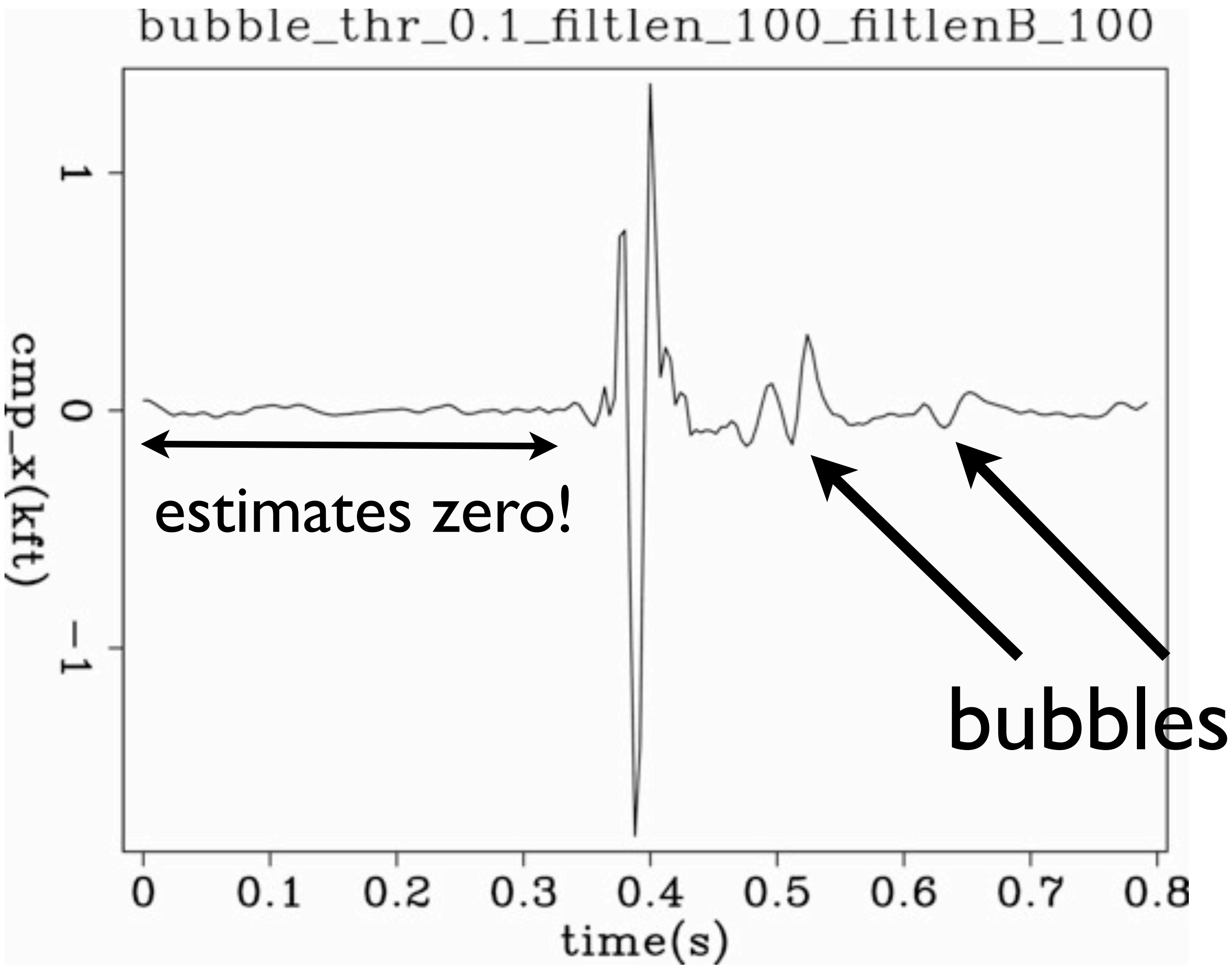
Bidirectional decon spikes on the <u>big middle lobe</u>.

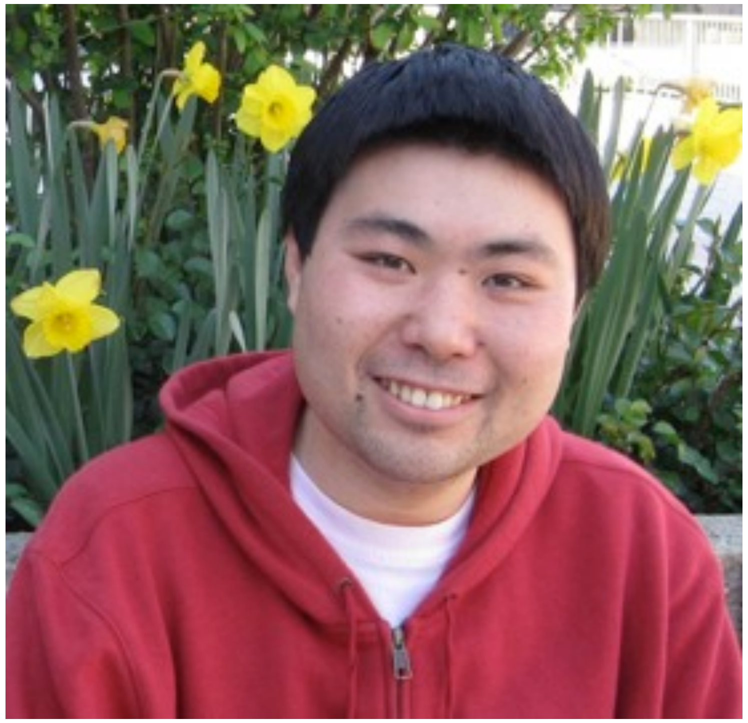
That explains the polarity jumping around!

$$\text{wavelet}(t) = \text{FT}^{-1} \frac{1}{A(Z)B(1/Z)}$$

where $Z = e^{i\omega t}$

Estimate of marine bubble

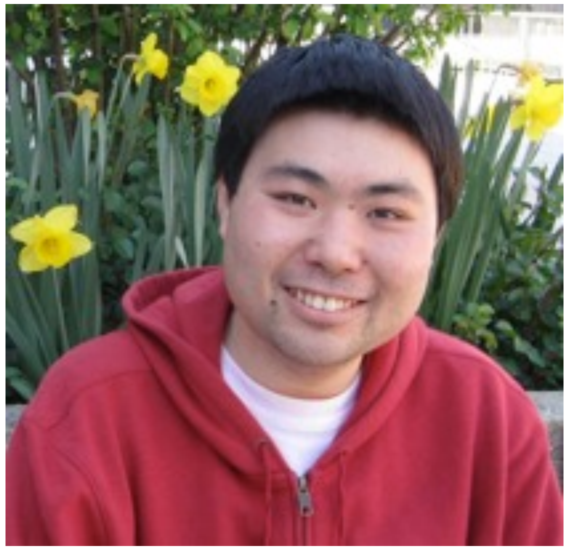




Inverse Ricker Wavelet is

a fun exercise with Z-transforms,
not difficult

but Qiang Fu will tell you about this.



Non linear problems demand

(1) good starting guess and
(2) cautious descent.

The <u>Slalom Method</u> works but is unsteady.

```
iterate{                    # easy to code
    fix a;  find b;    # old linear
    fix b;  find a;    # likewise
    }
```

With L2 norm, output tends to white.

$$
\begin{aligned}
\mathbf{0} &\approx [d * a]\ \mathbf{b}^r \\
\mathbf{0} &\approx [d * b^r]\ \mathbf{a}
\end{aligned}
$$

a and b fight for control of the spectrum of d.

Non linear problems demand

(1) good starting guess and
(2) cautious descent.

$$r = d * (a + \Delta a) * (b^r + \Delta b^r)$$
$$\min(\Delta a, \Delta b) = \mathrm{hyp}(r)$$

Yi Shen will tell you more about <u>symmetric descent</u>.

Linear problems are like a walk in the city.
There are people all over.
If you get lost, you can ask almost anyone.

Linear problems are like a walk in the city.
There are people all over.
If you get lost, you can ask almost anyone.

Nonlinear problems like a trek in a dark jungle.
Almost nobody around. You might find treasure.
But strange creatures might sneak up and bite you.

Non linear problems demand

(1) good starting guess and
(2) cautious descent and
(3) preconditioning.

Preconditioning guides non-linear regression away from unwelcome local minima.

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Preconditioning guides non-linear regression away from unwelcome local minima.

Do usual PEF first, then bidecon the PEF output.

ASPIRATIONS

(1) Establish a stable method, and identify limitations of bidirectional decon

(2) Time integrate the reflectivity to get a blocky impedance function.

(3) Use helix filters to get the space-dependent waveform

$$\text{wavelet}(\omega) \text{ is usual}$$

$$\text{wavelet}(k_x) \text{ is array}$$

$$\text{wavelet}(k_x/\omega) \text{ is ghost}$$

CONCLUSIONS

Antoine Yi Shen Qiang Fu Jon

It's still fun.
Many exciting prospects remain.
Immediate goals to explore opportunities and pitfalls.

Thanks to:

Yang Zhang

Yunyue (Elita) Li

Yi Shen

Qiang Fu

Mandy Wong

Ali Almomin

Antoine Guitton

Bob Clapp

Shuki Ronen


Fu
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