Time domain IM prediction

using a nonstationary search parameter ε

Kris Innanen

Dec 3 2015
CREWES Annual Meeting
Banff, AB

UNIVERSITY OF CALGARY

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Outline

Motivation and review

i. The land internal multiple problem
ii. Review: IM prediction and ε
iii. Approach: domain and nonstationarity

Time domain internal multiple prediction

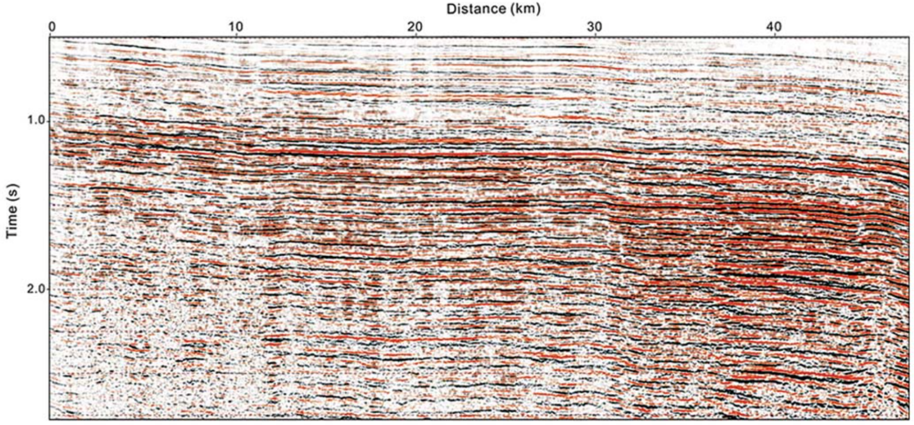
i. Time domain prediction formula
ii. Algorithm

Time-nonstationarity of the search parameter ε

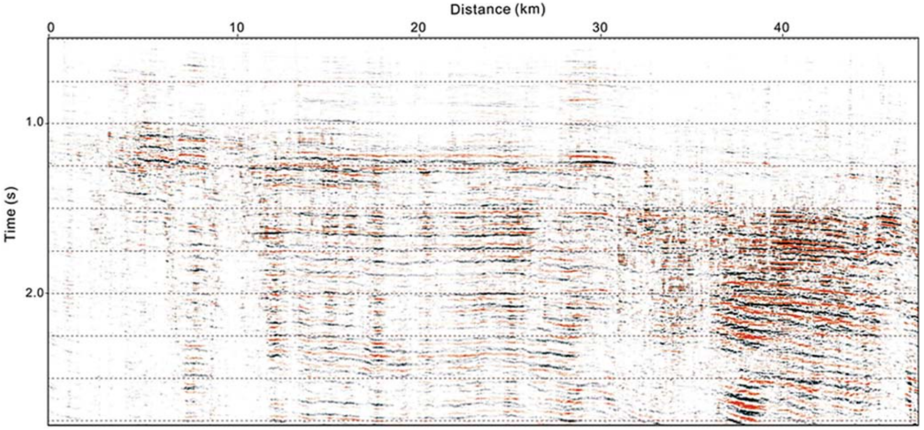
i. The basic idea
ii. Data driven $\varepsilon(t)$: synthetic example
iii. Model based selection of $\varepsilon(t)$: laboratory example

Motivation and review

The land internal multiple problem



Input



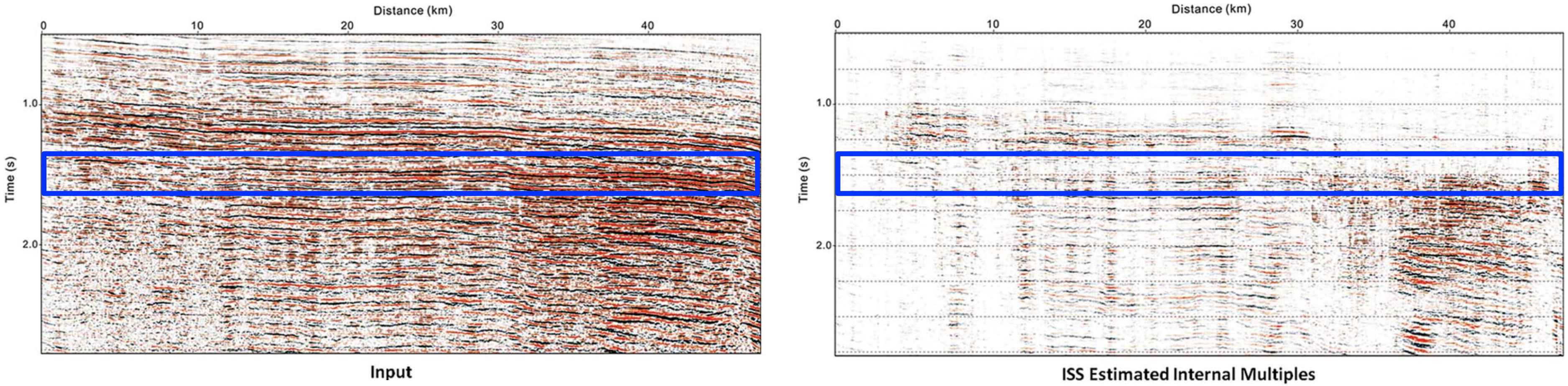
ISS Estimated Internal Multiples

Luo et al., 2011 TLE

Inverse scattering series method (Weglein, Araujo, Coates, etc., 1990s)

Motivation and review

The land internal multiple problem



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Motivation and review

The land internal multiple problem

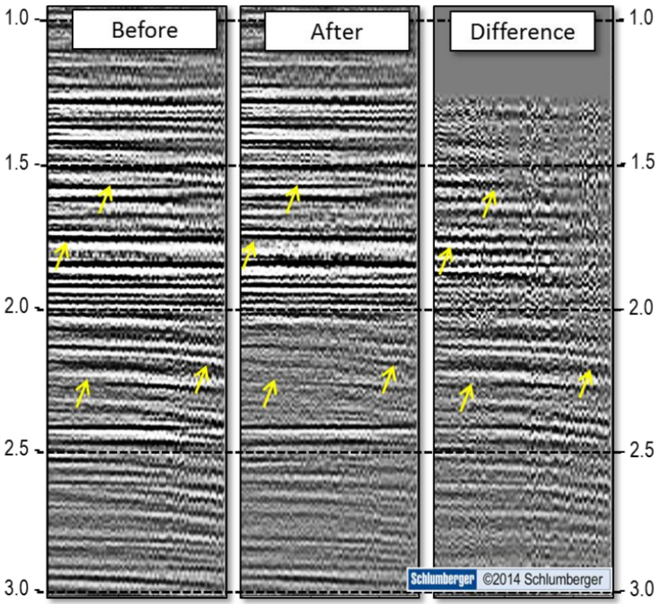
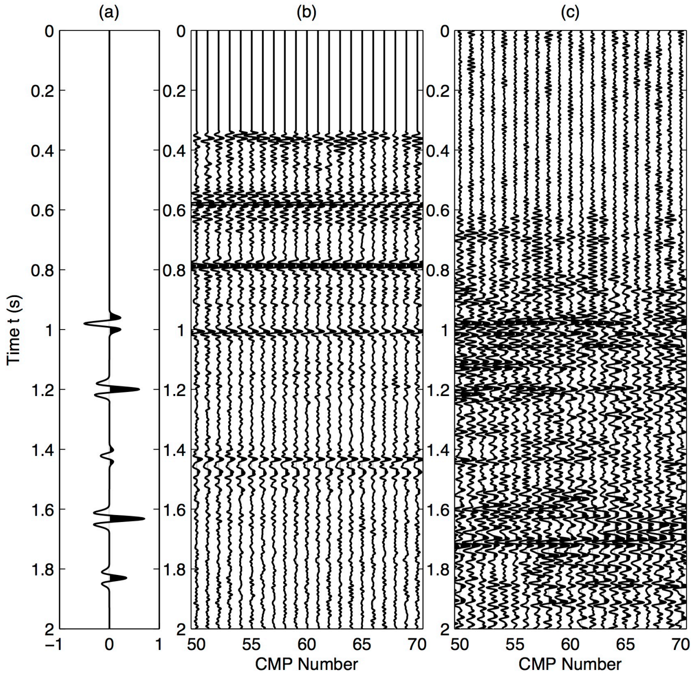


Figure 3 – CMP gathers before and after ISS multiple attenuation. Arrows indicate where strong multiples were removed. Gather difference shows strong multiples that were attenuated.

de Melo et al., 2014 SEG Abstracts



Hernandez & Innanen, 2014 CJEG

Motivation and review

The land internal multiple problem

Land data issues

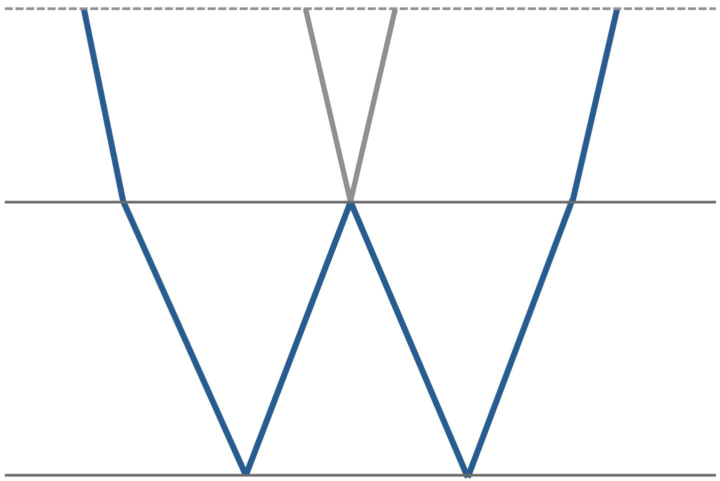
i. Noise, near-surface generators
ii. Closely-spaced generators and sub-events
iii. Predictions with lots of distributed energy

Prediction issues

i. Closely-spaced sub-events cause artifacts
ii. Artifacts are correlated with primary arrivals
iii. Fix with selection of a more “cautious” ε, but
iv. Cautious ε selection leads to missed predictions

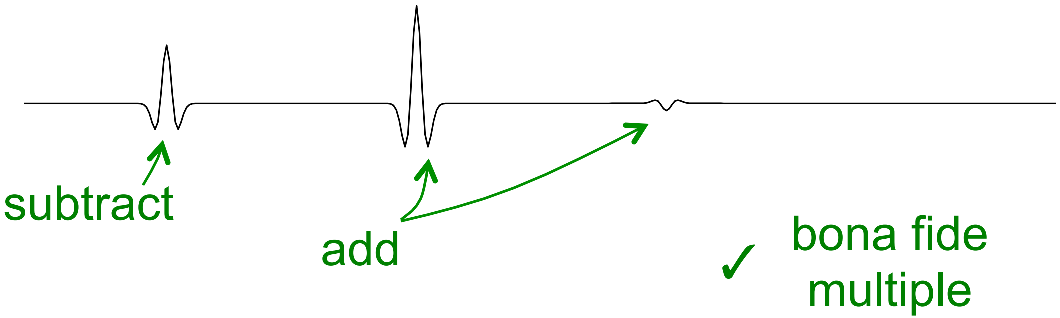
Motivation and review

Review: IM prediction by (i) *combining sub-events*, (ii) *limited by* ε



$$t_{im} = t_{p1} + t_{p2} - t_{p3}$$

$$\mathrm{IM}(\omega) = \int dt e^{i\omega t} s(t) \int_{-\infty}^{t} dt' e^{-i\omega t'} s(t') \int_{t'}^{\infty} dt'' e^{i\omega t''} s(t'')$$



Motivation and review

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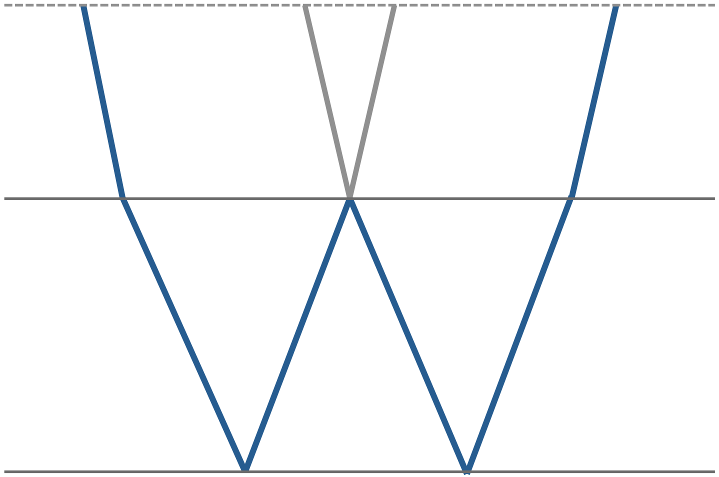

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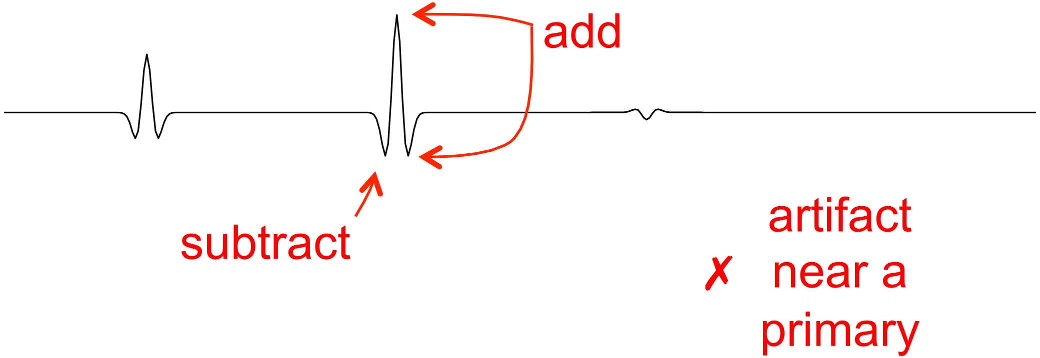
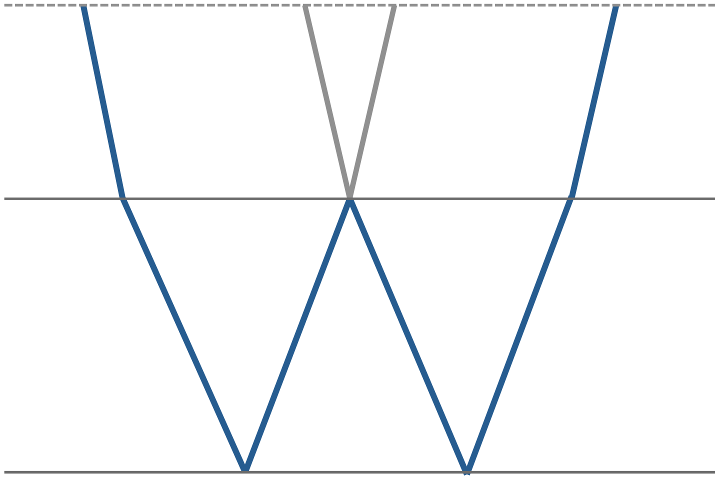


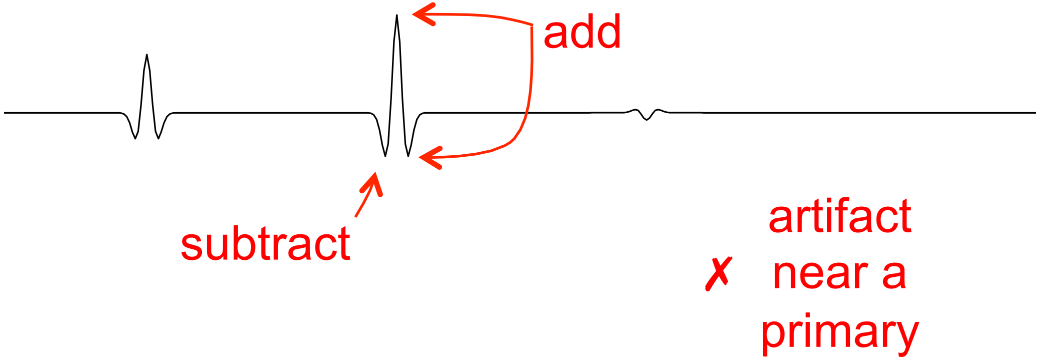
Motivation and review

Review: IM prediction by (i) *combining sub-events*, (ii) *limited by ε*



$$t_{im} = t_{p1} + t_{p2} - t_{p3}$$

$$\mathrm{IM}(\omega) = \int dt e^{i\omega t} s(t) \int_{-\infty}^{t-\epsilon} dt' e^{-i\omega t'} s(t') \int_{t'+\epsilon}^{\infty} dt'' e^{i\omega t''} s(t'')$$



Fix: min separation ε between events is enforced

Motivation and review

Summary

$$\mathrm{IM}(\omega) = \int dt e^{i\omega t} s(t) \int_{-\infty}^{t-\epsilon} dt' e^{-i\omega t'} s(t') \int_{t'+\epsilon}^{\infty} dt'' e^{i\omega t''} s(t'')$$

Data trace $s(t)$ appears three times, convolved/correlated

Output domain is frequency: "ω domain prediction"

Parameter ε must be selected (f_{dom} as initial guide)

ε must be constant w.r.t. all activity on the right hand side

...which leaves open the possibility of $\varepsilon = \varepsilon(\omega)$.

Motivation and review

Approach: seek improvements in IMP precision, focusing on:

Domain of prediction

- k_g-ω, k_g-k_s-ω (standard: Araujo, Weglein, 1994-97)
- τ-p (Coates & Weglein, 1996; Sun et al., 2015)
- τ-p_g-p_s (Sun et al., 2015; 10:50am)
- k_g-t, x_g-t (this presentation)

Nonstationarity

- in adaptive subtraction (Keating et al., 2015; 11:15am)
- in prediction parameter ε (this presentation)

Time domain prediction

$$\beta(t) = t - \epsilon$$

$$\mathrm{IM}(t) = \int_{-\infty}^{\infty} dt' s(t'-t) \int_{\alpha(t,t')}^{\beta(t)} dt'' s(t'-t'') s(t'')$$

$$\alpha(t,t') = t' - (t - \epsilon)$$

The idea of "restricted convolution/correlation" maintained.

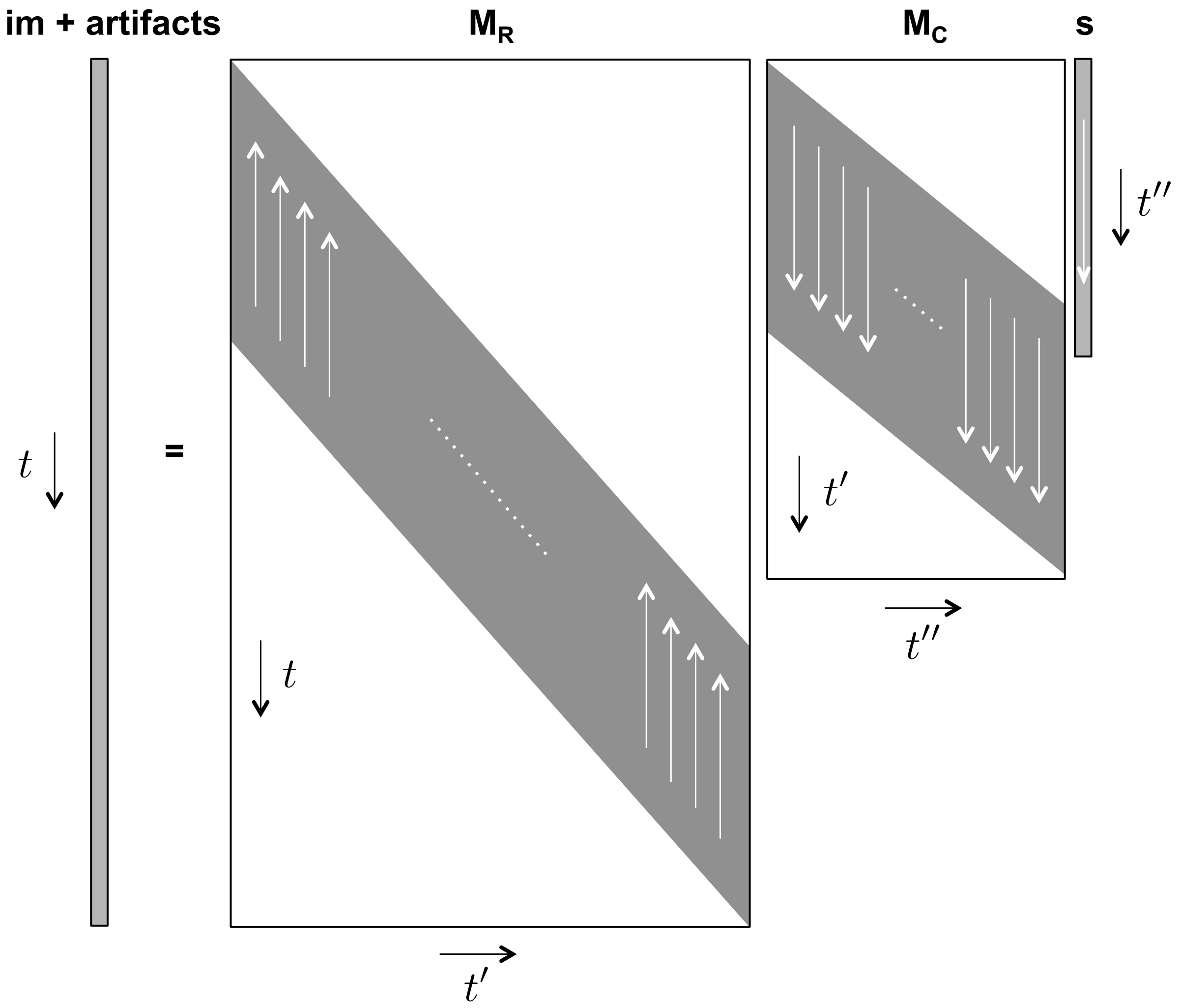
Time domain prediction

Start with α=-∞, β=∞ to devise an efficient algorithm:

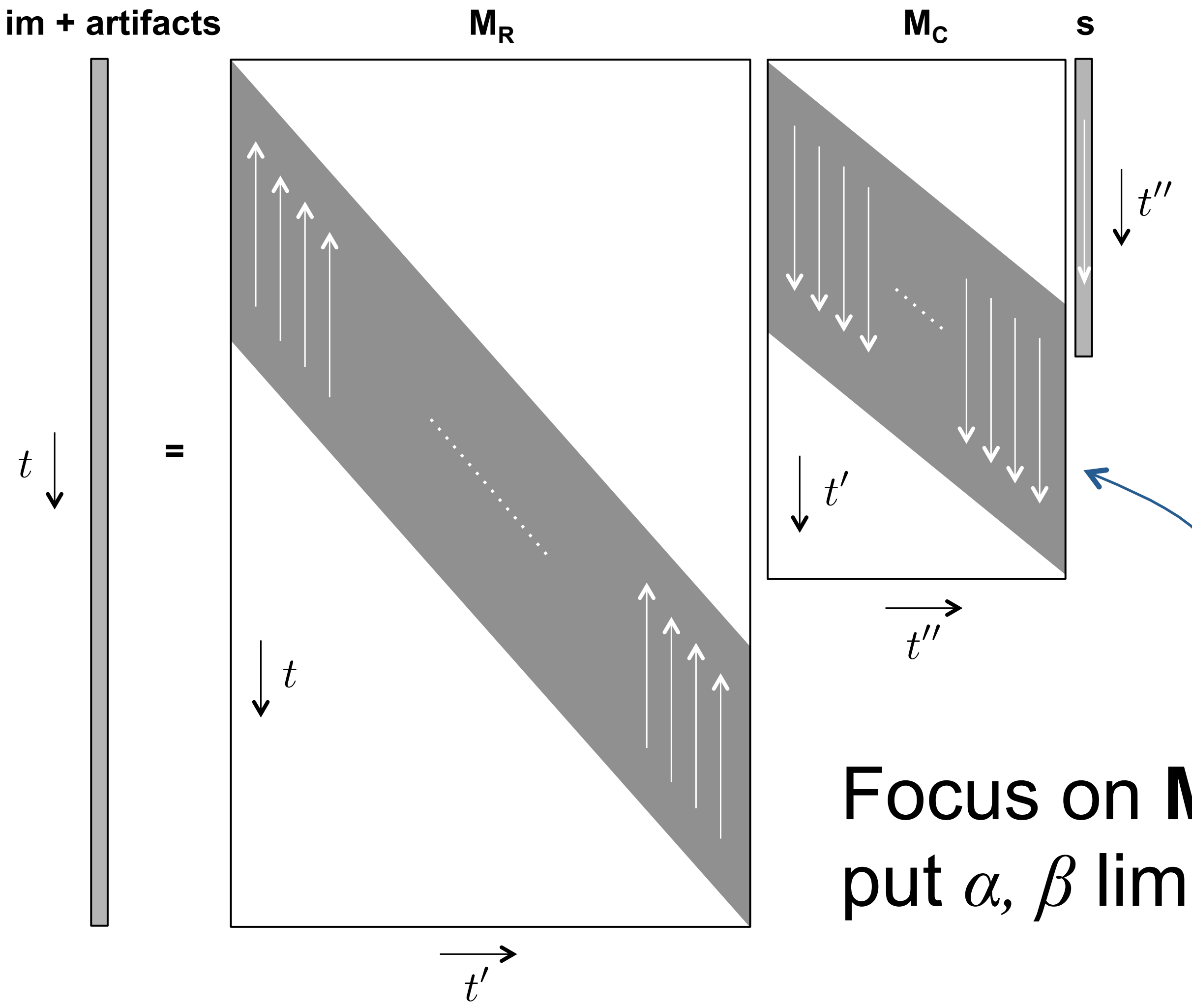
$$\mathrm{IM}(t) + \mathrm{artifacts} = \int_{-\infty}^{\infty} dt' s(t'-t) \int_{-\infty}^{\infty} dt'' s(t'-t'') s(t'')$$

$$\downarrow$$

$$\mathbf{im} + \mathrm{artifacts} = \mathbf{M}_{\mathrm{R}} \mathbf{M}_{\mathrm{C}} \mathbf{s}$$

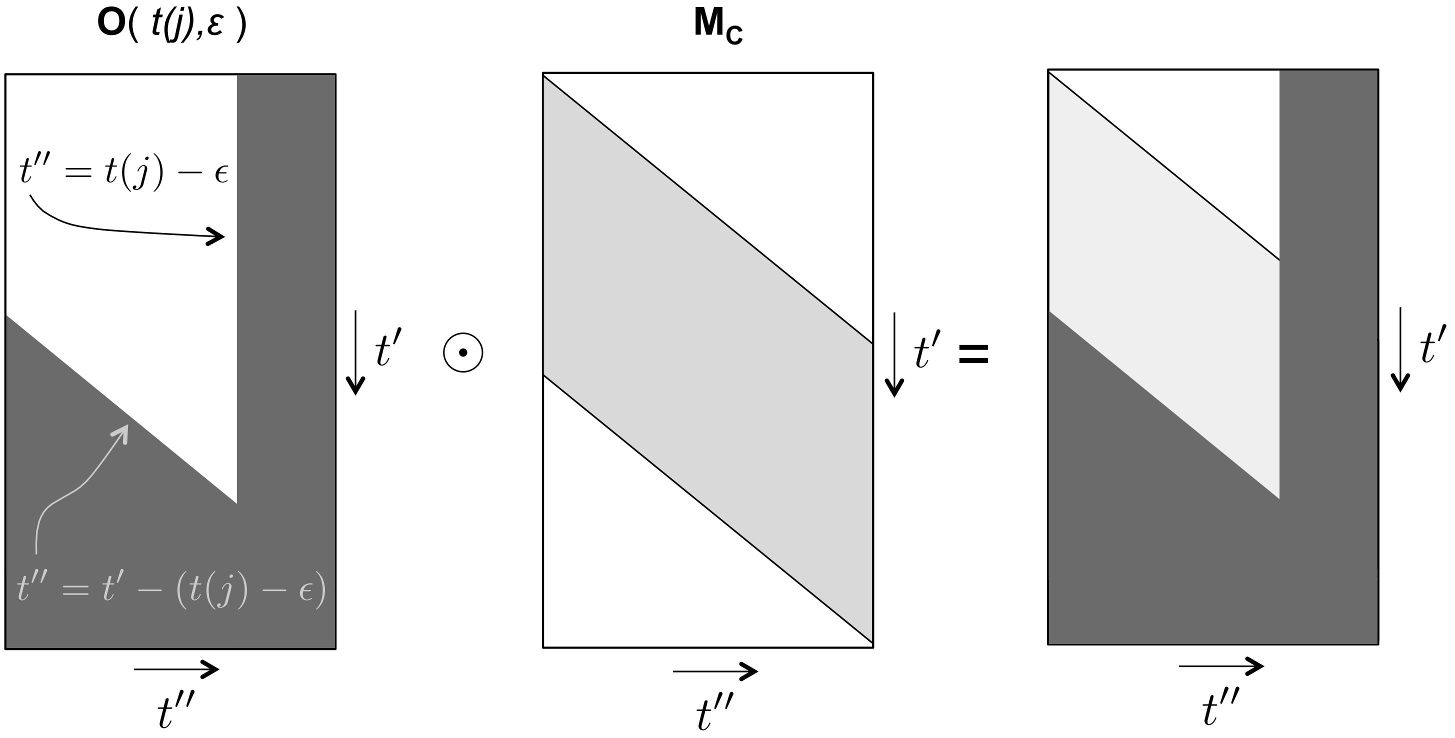


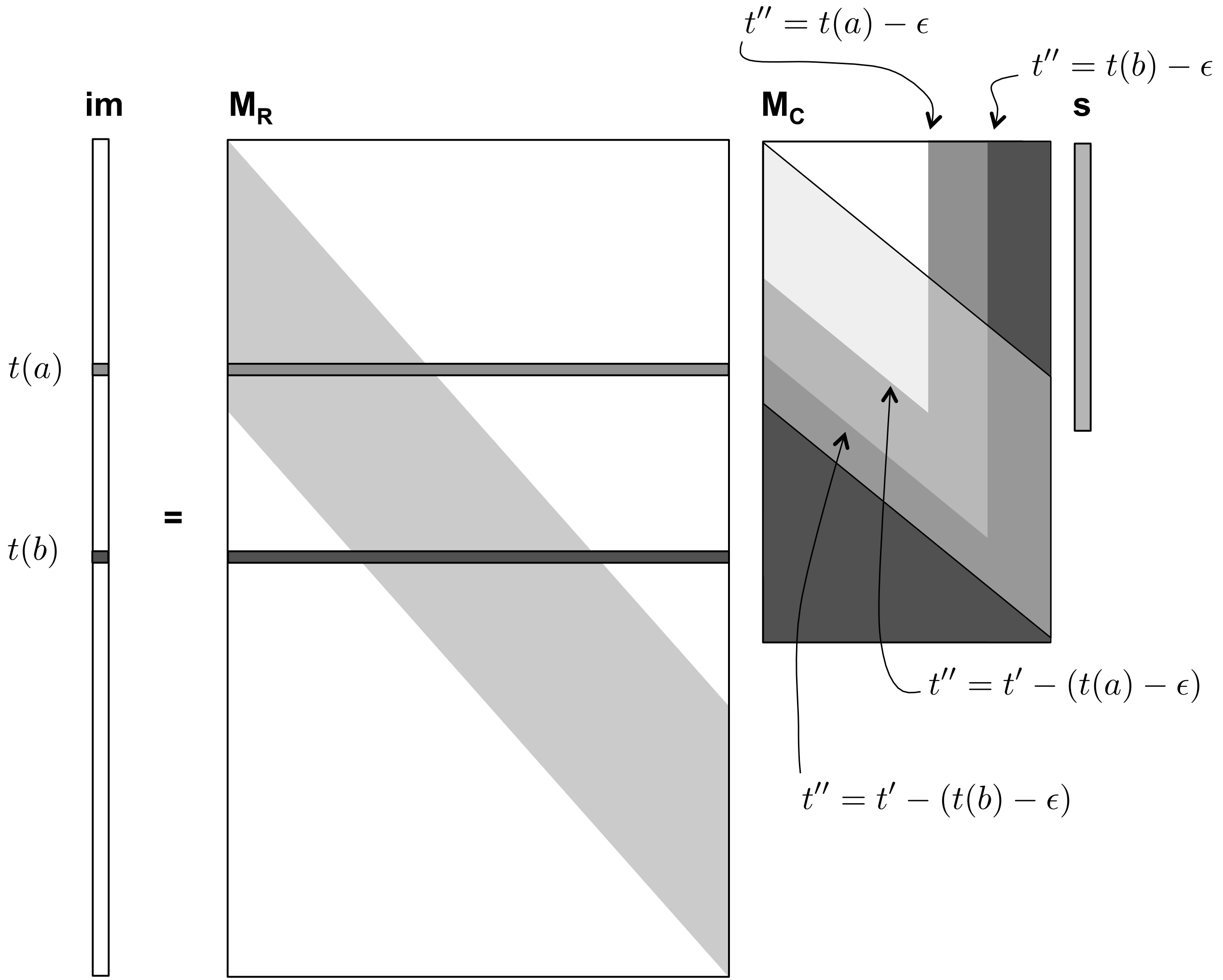
im + artifacts
$\mathbf{M_R}$
$\mathbf{M_C}$
s
t
=
t
t'
t'
t''
t''



Focus on $\mathbf{M_c}$ next:
put α, β limits back in

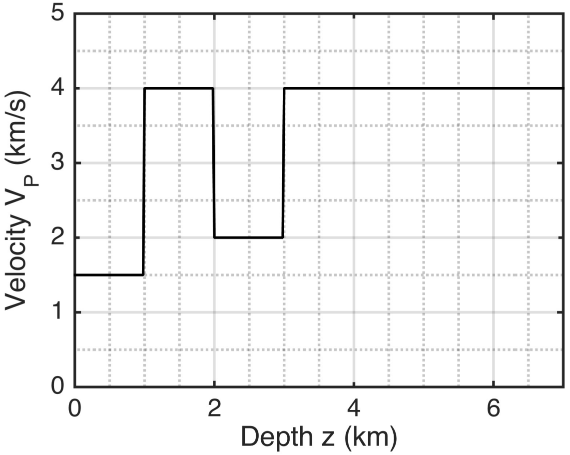
$$\mathrm{IM}(t) = \int_{-\infty}^{\infty} dt' s(t'-t) \int_{\alpha(t,t')}^{\beta(t)} dt'' s(t'-t'')s(t'')$$



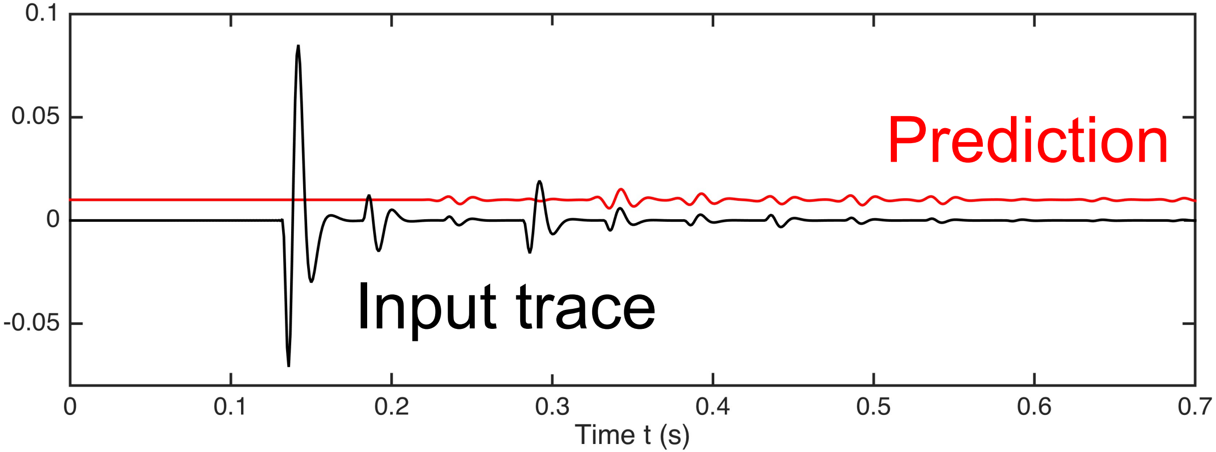


im
$\mathbf{M_R}$
$\mathbf{M_C}$
s
$t(a)$
$t(b)$
=
$t'' = t(a) - \epsilon$
$t'' = t(b) - \epsilon$
$t'' = t' - (t(a) - \epsilon)$
$t'' = t' - (t(b) - \epsilon)$

Time domain prediction

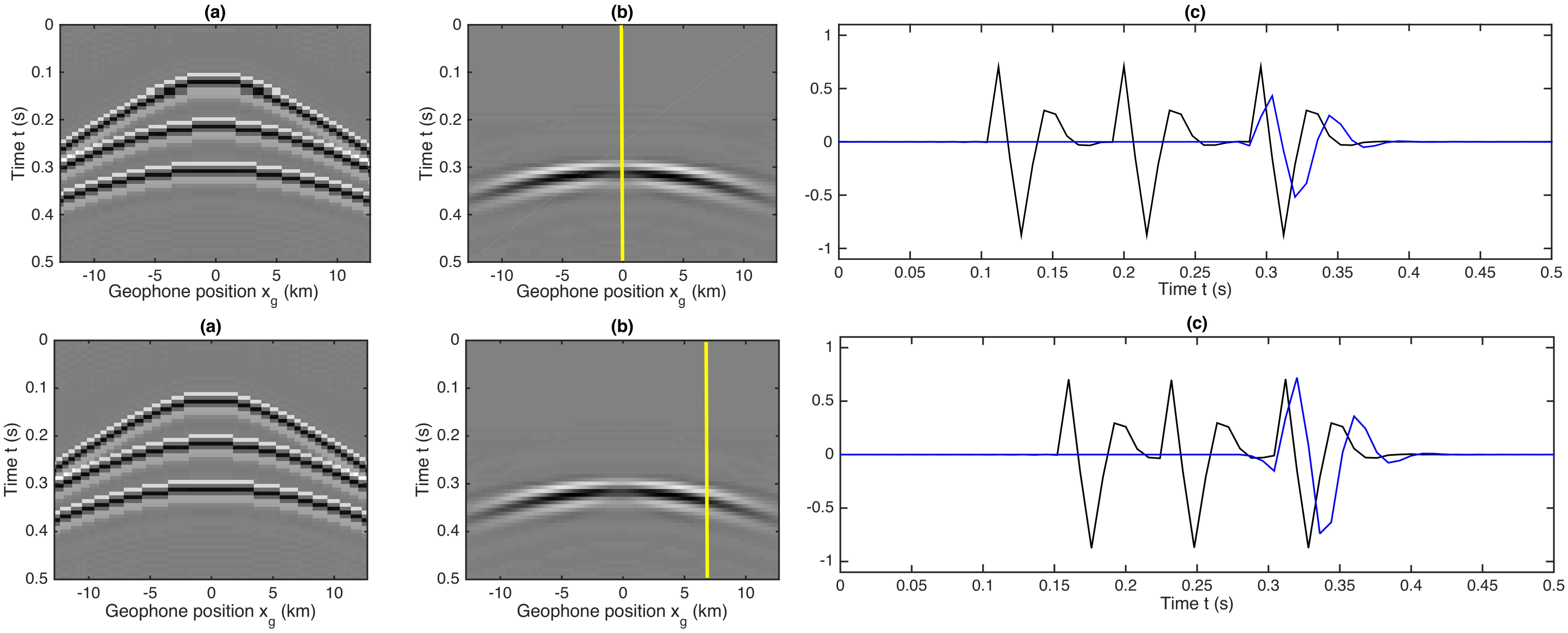


Velocity model



Time domain prediction

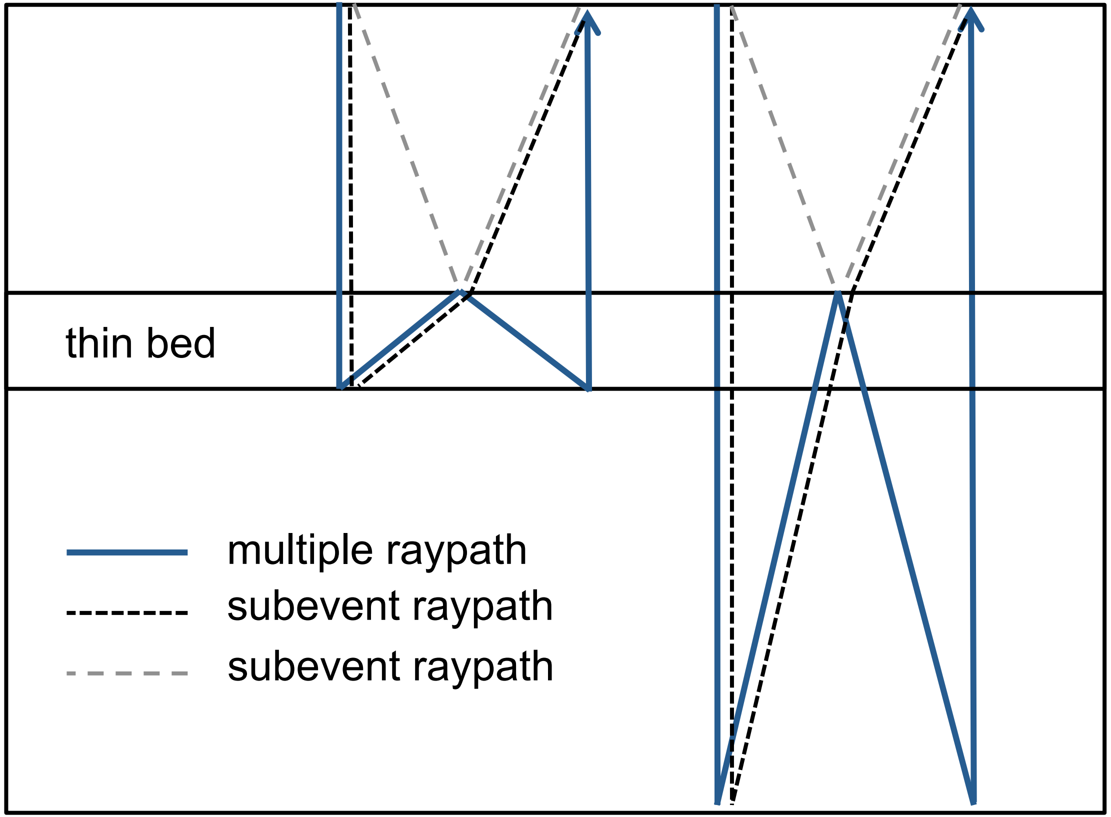
$$\mathrm{IM}(x_g,t)=\int dx'\int dt' s(x_g-x',t'-t)\int dx''\int_{\alpha(t,t')}^{\beta(t)} dt'' s(x'-x'',t'-t'')s(x'',t'')$$



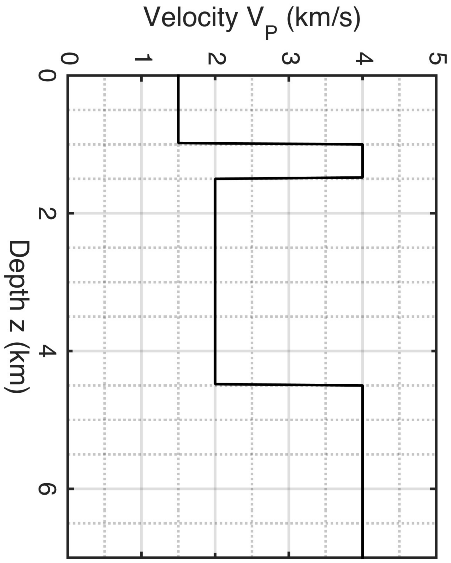
The time nonstationarity of ε

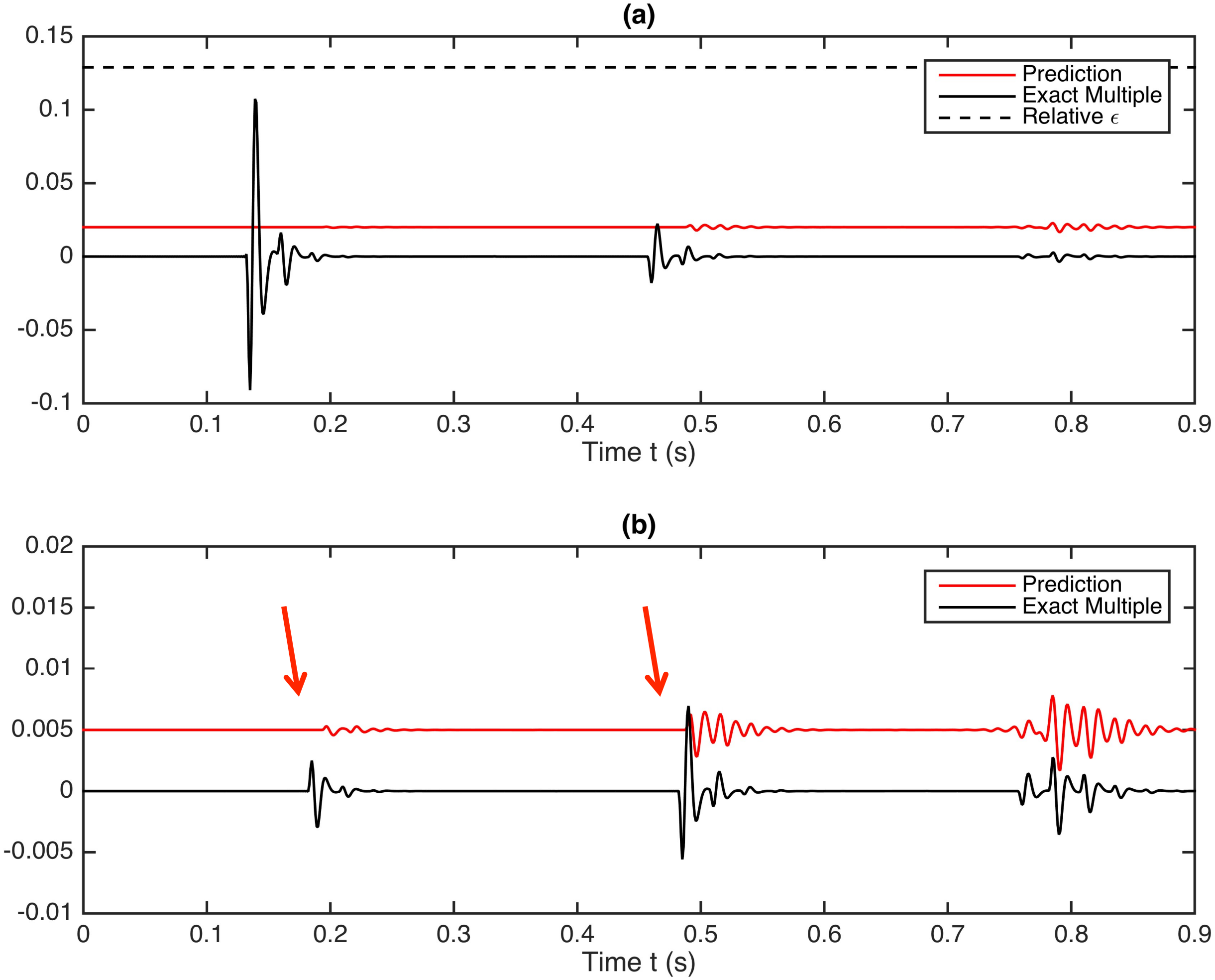
Thin bedding, for example, imposes nonstationarity on the proximity of sub-events.

Optimum ε varies with proximity of sub-events

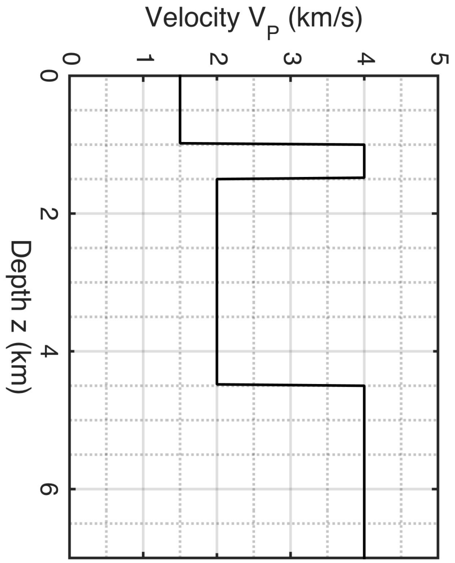


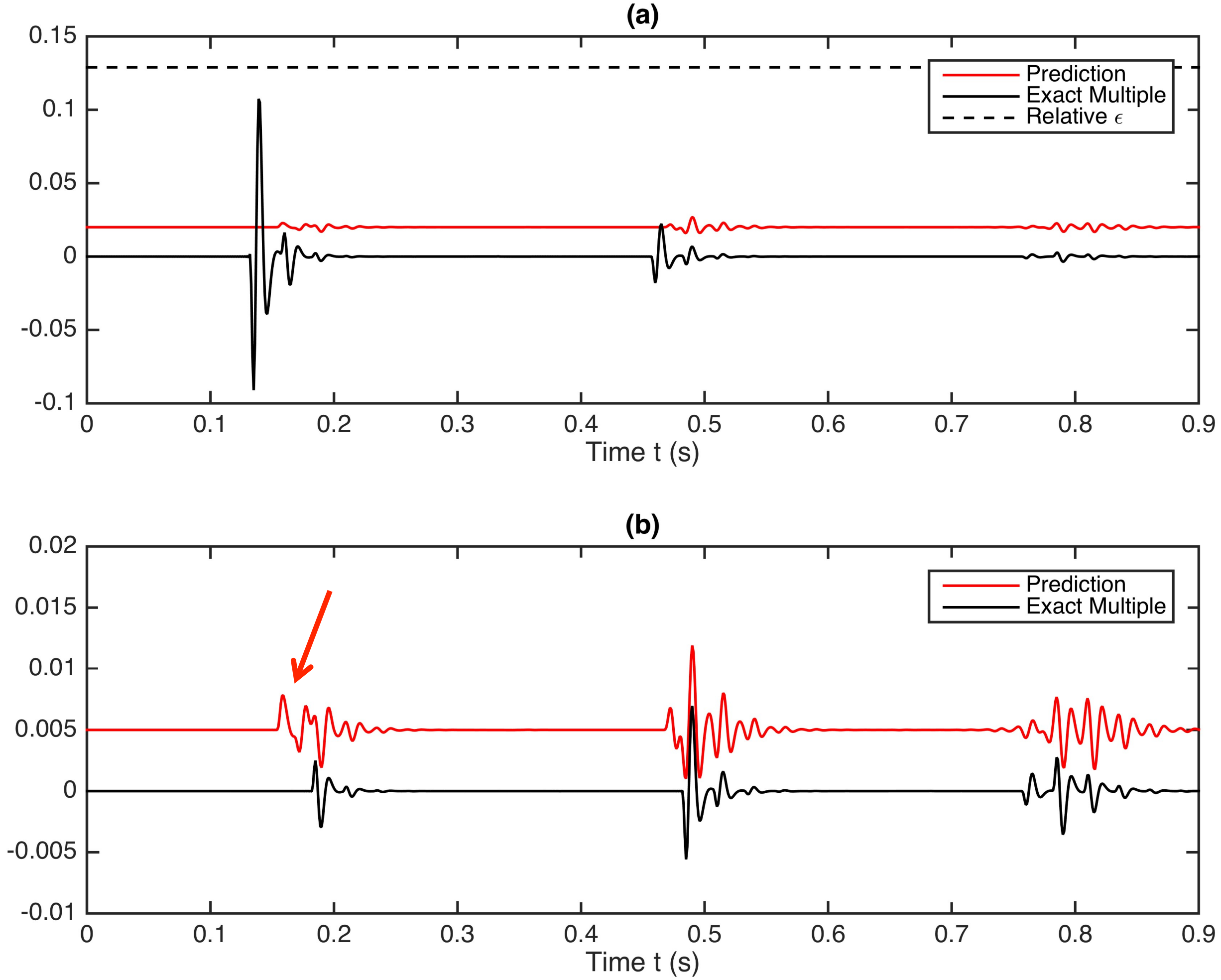
Stationary ε
"cautious"



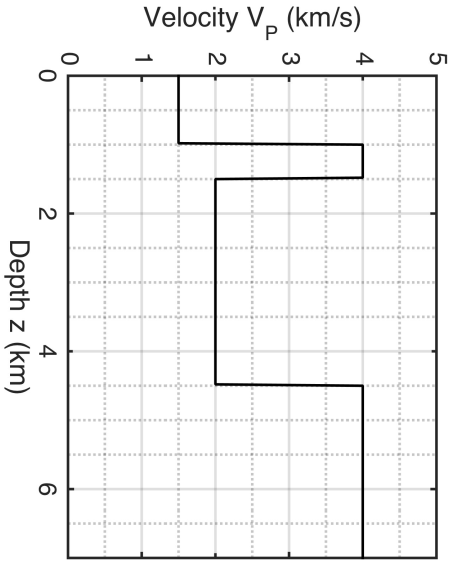


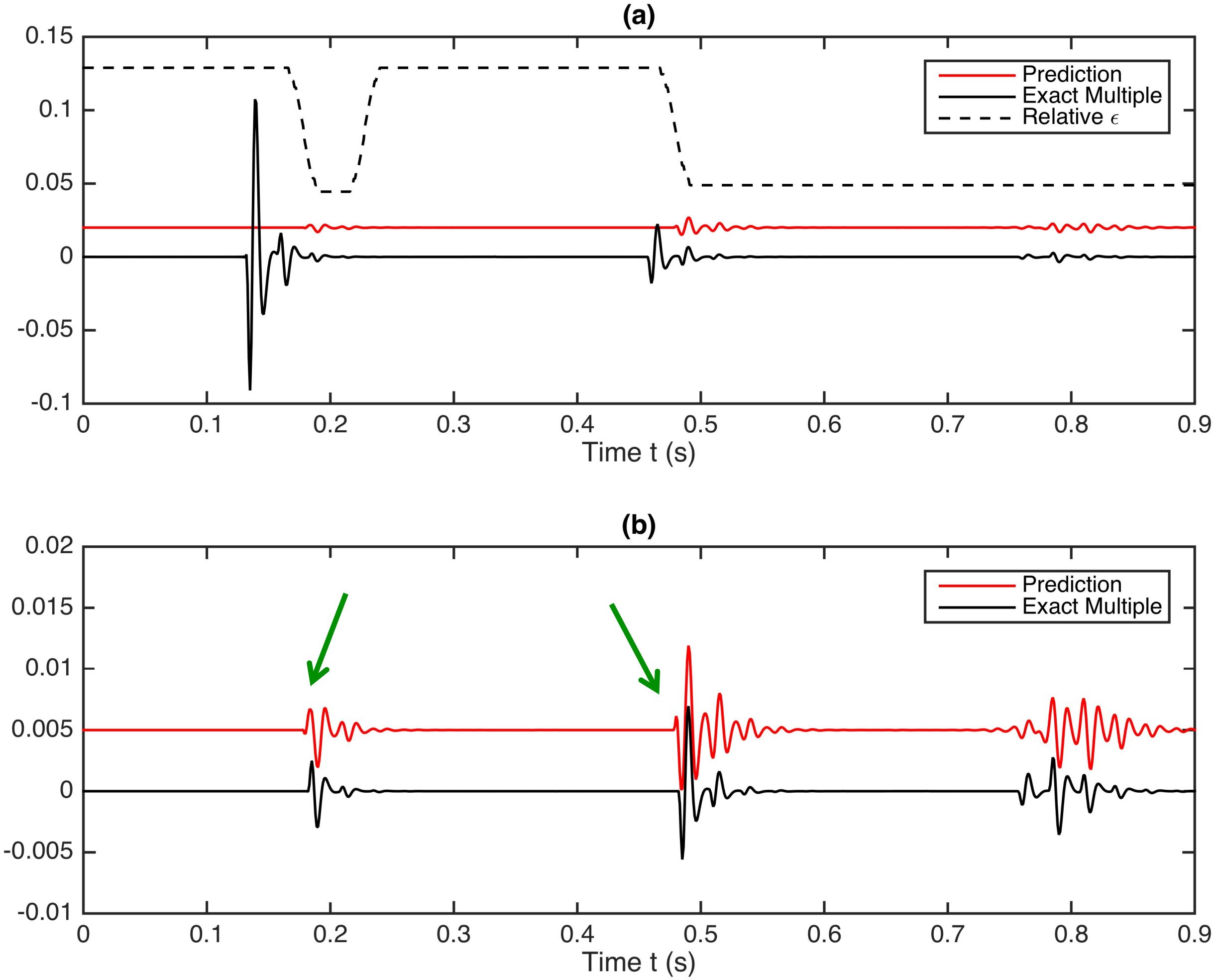
Stationary ε
“aggressive”





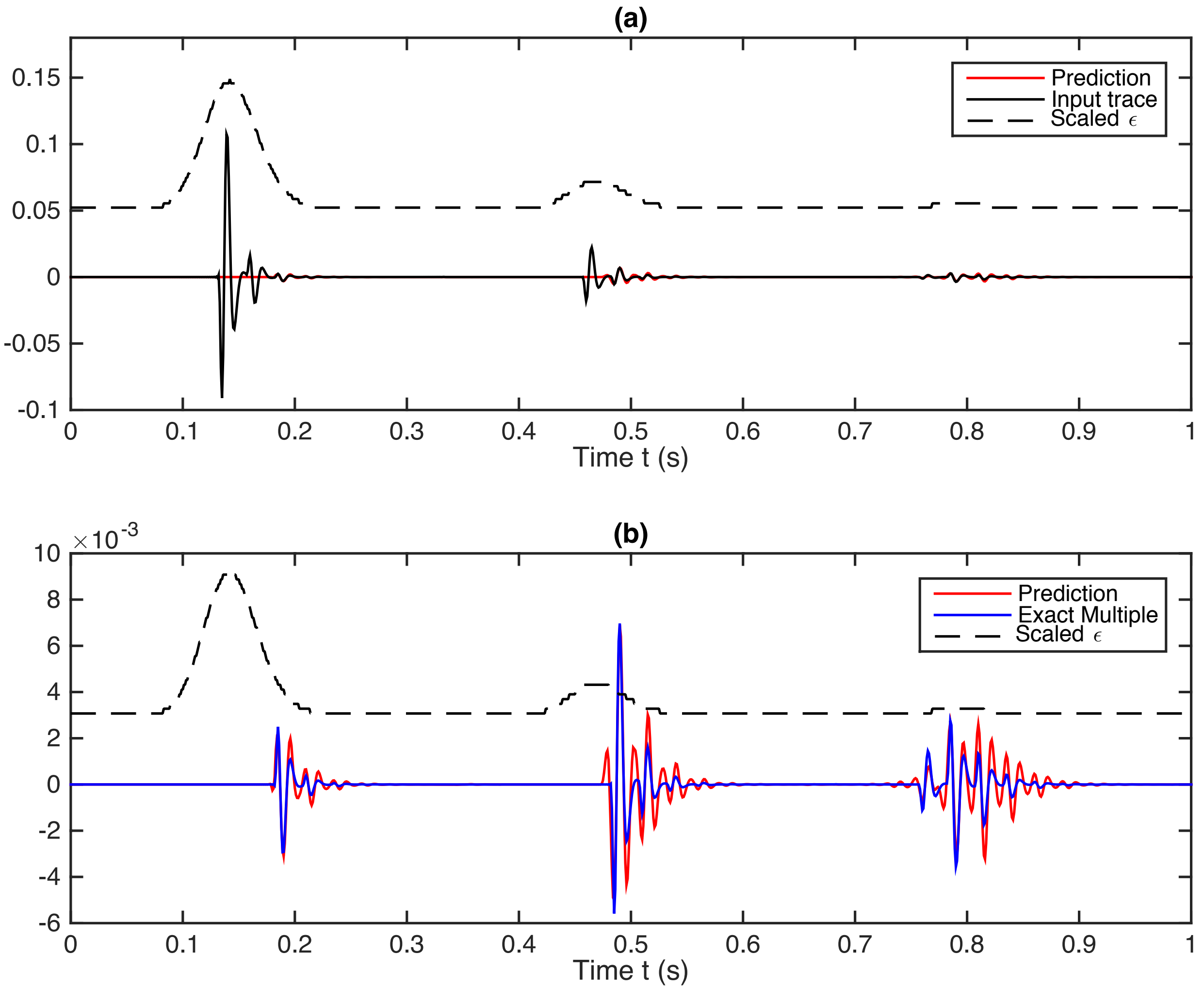
Nonstationary ε



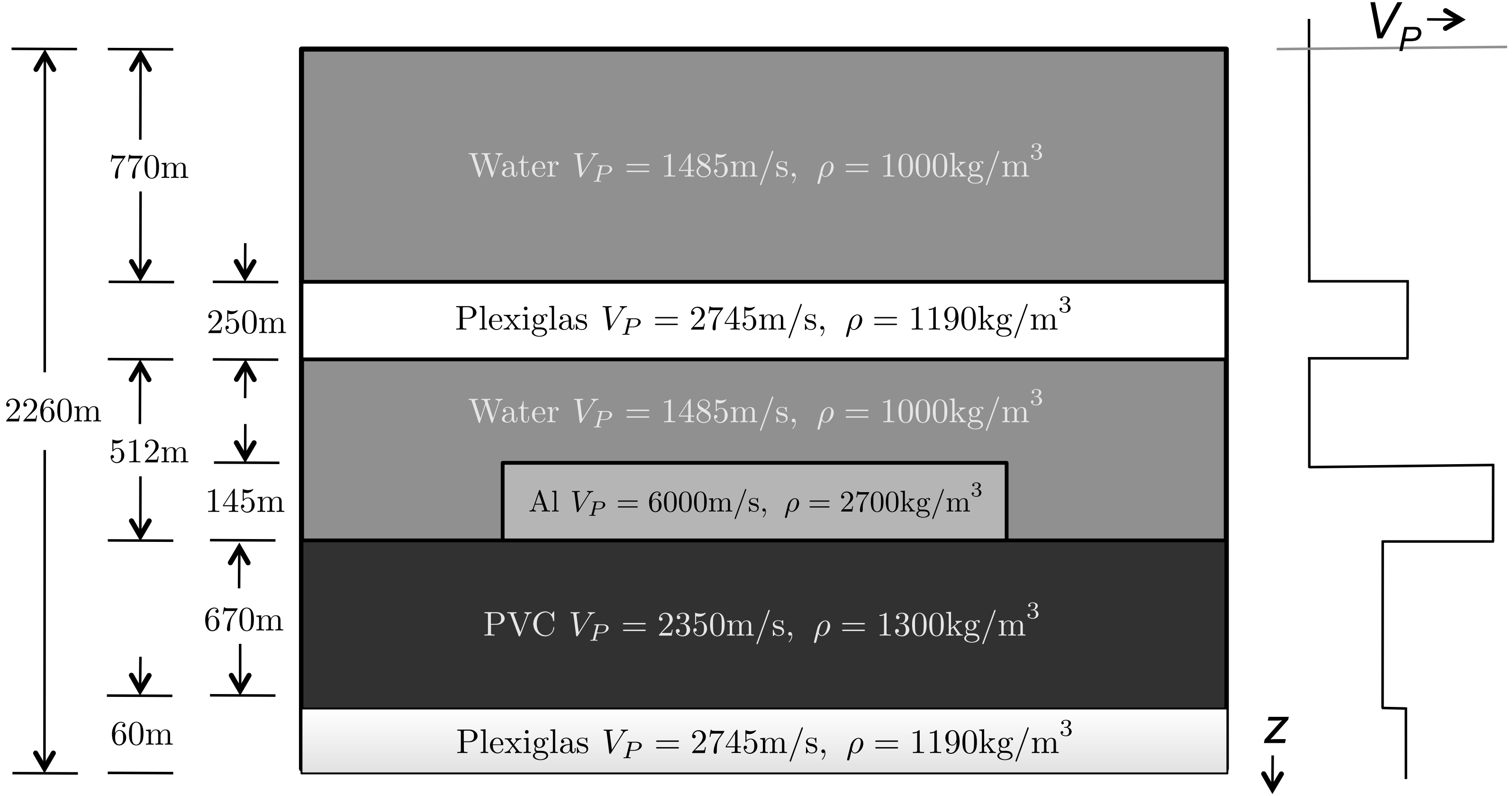


Selection of $\varepsilon(t)$

Data driven $\varepsilon(t)$ - smoothed Hilbert envelope of the trace.

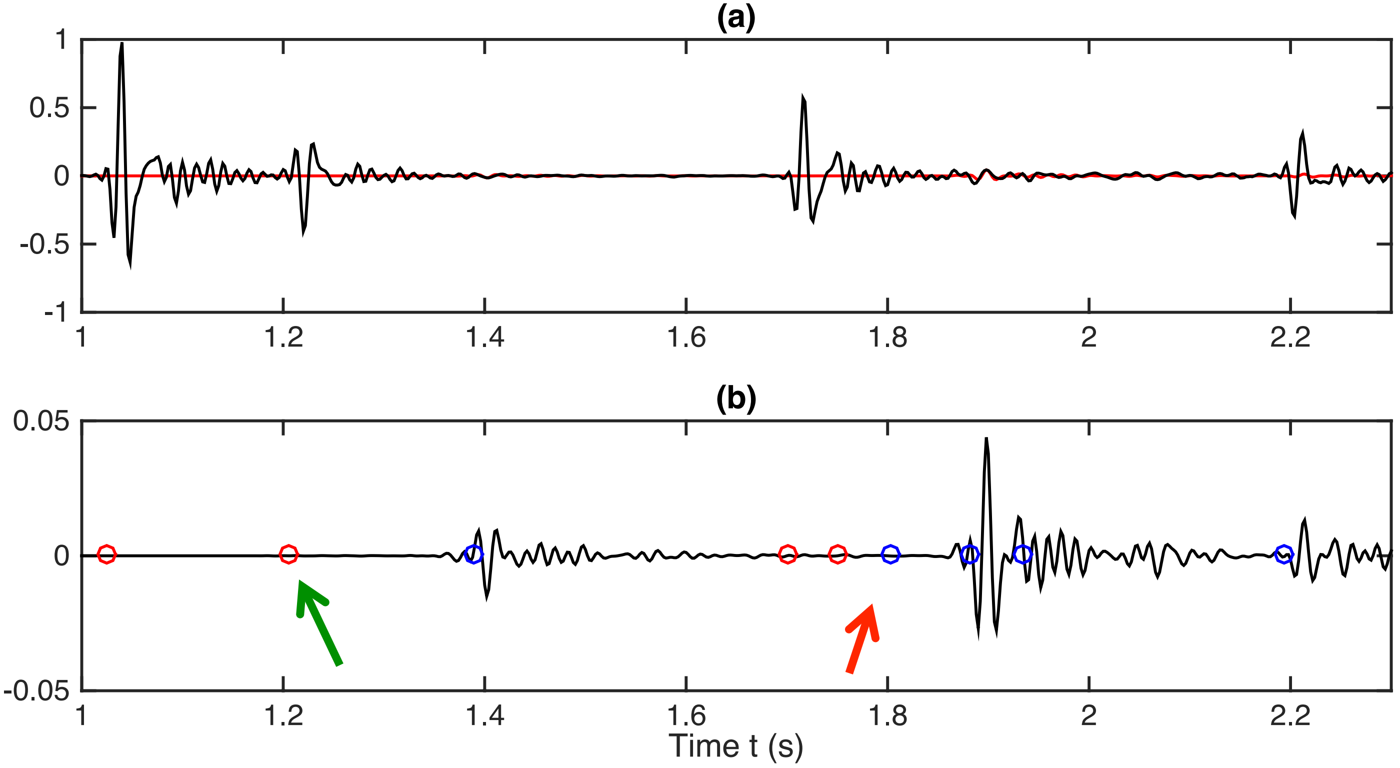


Selection of *ε(t)*: geological information



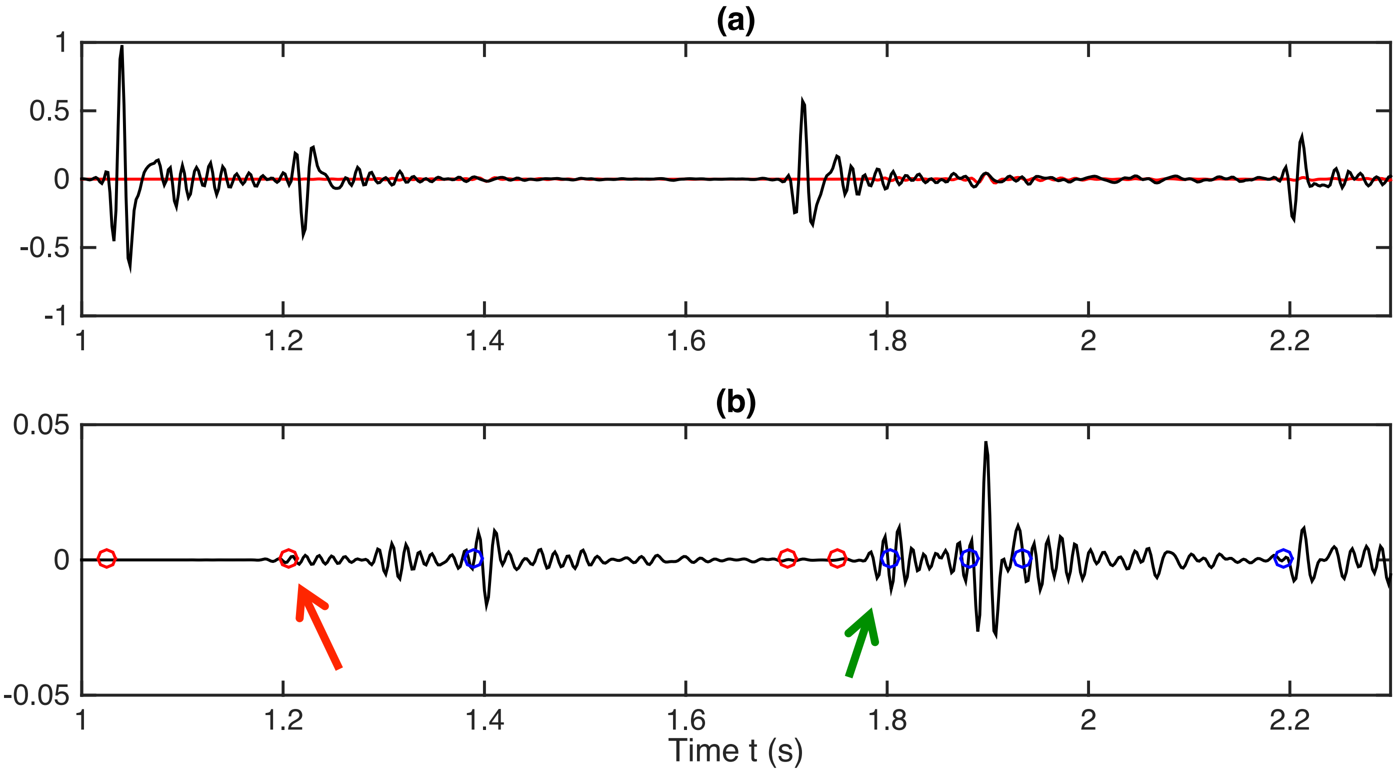
Physical modelling data set (e.g., Hernandez, 2012)

Stationary ε - *too large*



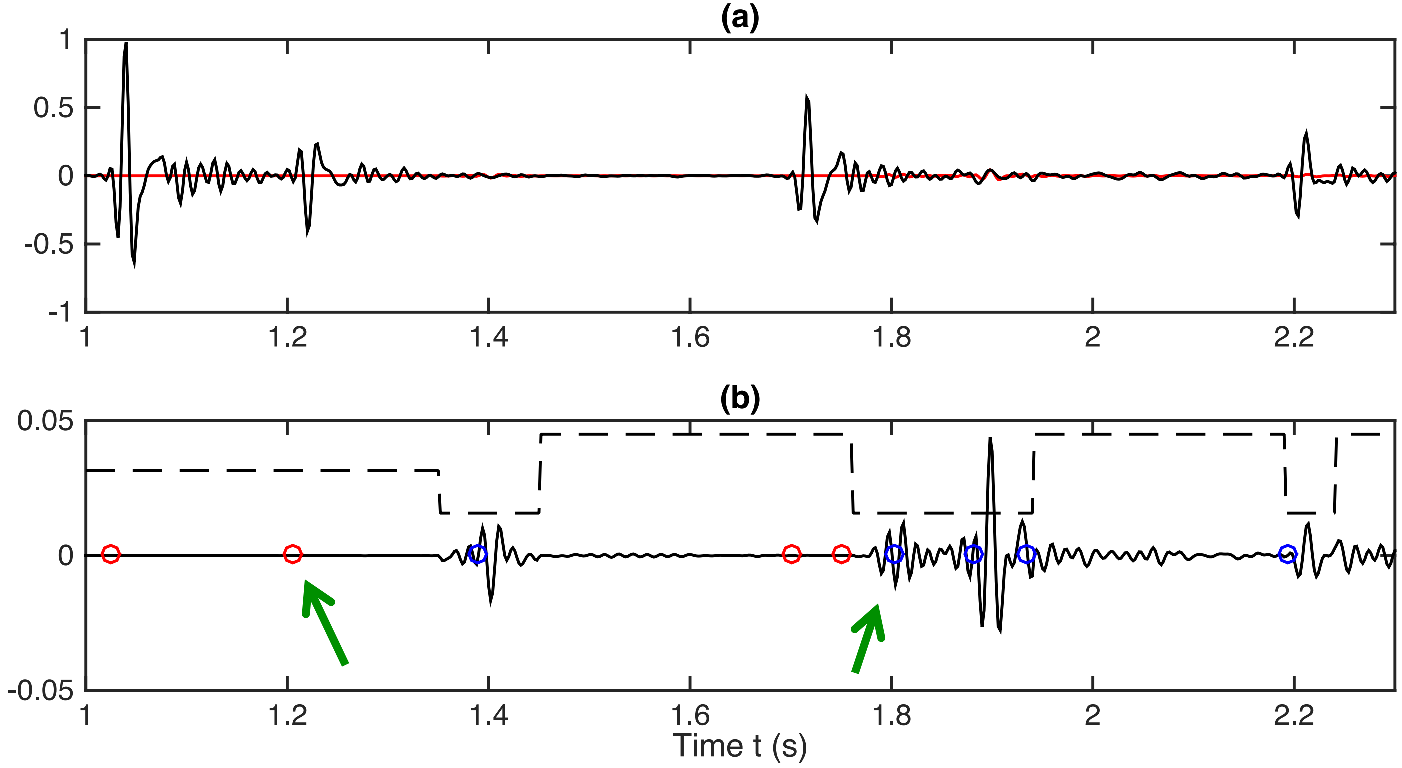
○ Expected IM arrival time ○ Expected P arrival time

Stationary ε - *too small*



○ Expected IM arrival time ○ Expected P arrival time

Nonstationary $\varepsilon(t)$ – *gauged by blocked log*



○ Expected IM arrival time ○ Expected P arrival time

Conclusions

Motivations: *internal multiples on land: ISS methods promising, but heightened precision needed.*

Possible approach: *vary domain of application, investigate resulting opportunities for increased prediction precision with nonstationary* ε.

Evidence: *synthetics and lab examples not difficult to produce which demonstrate the potential of* $\varepsilon(t)$.

Call for input

Possible CREWES field experiment (~ Fall 2016) focused on validating 1D, 1.5D, 2D internal multiple prediction and adaptive subtraction developments.

Seeking: location ideas, interest in collaboration, multiple instrument types, etc.

Far-reaching: multicomponent demultiple workflow, incorporation of near-surface characterization research.

Acknowledgments

2014 example used Nexen NEBC Data set
Melissa Hernandez, Jian Sun, Scott Keating,
Penny Pan

CREWES

NSERC-CRD (CRDPJ 461179-13)