

MULTIPLE PREDICTION FROM INCOMPLETE DATA

Context

Claerbout Daylight imaging

Weglein's (inverse) series expansions

Verschuur and Berkhout's SRME and data inverse

Wapenaar's reciprocity relations

Motivation

Prediction of multiples requires **complete** data.

Success of primary-multiple **separation** depends on **quality** multiple prediction.

So far our interpolation algorithms lacked “physics”

We know from the wave equation

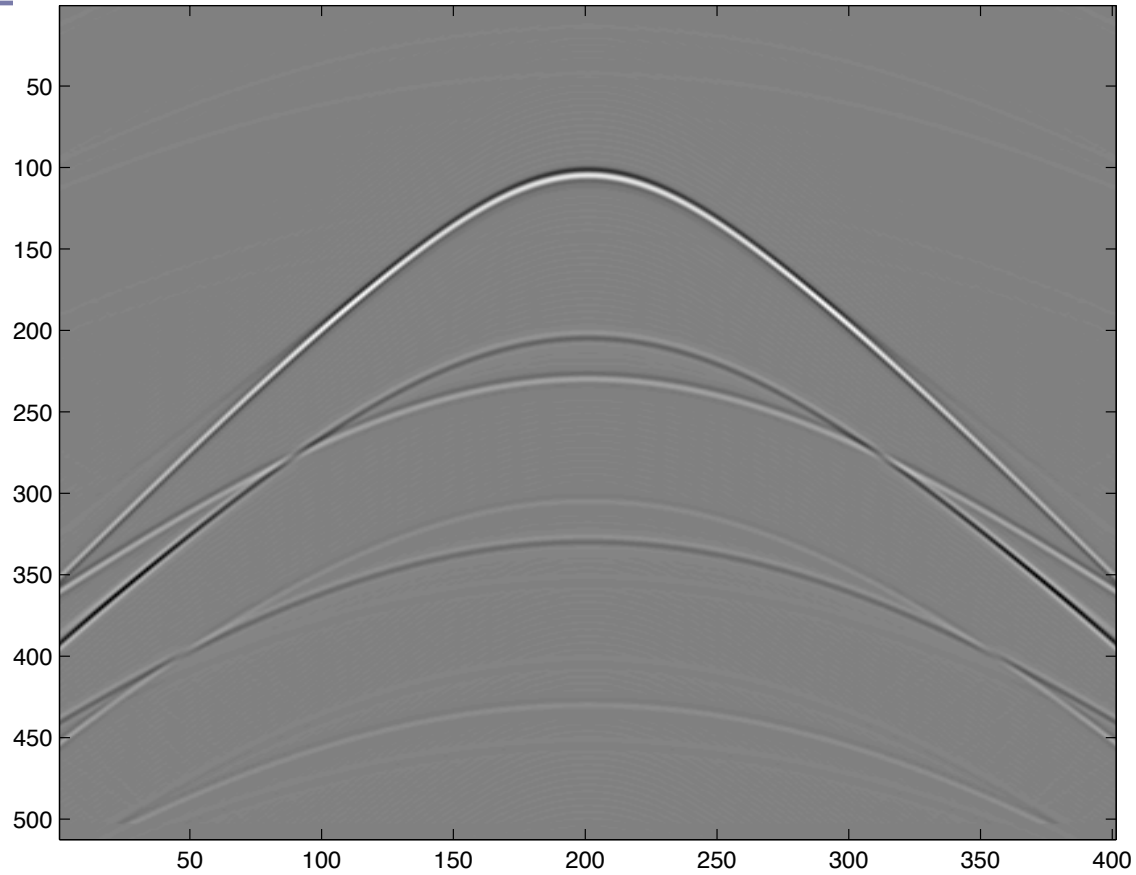
- reciprocity relations (convolution/correlation)
- primaries can be mapped to multiples and *vice versa*

Physics is often “naive” and non robust.

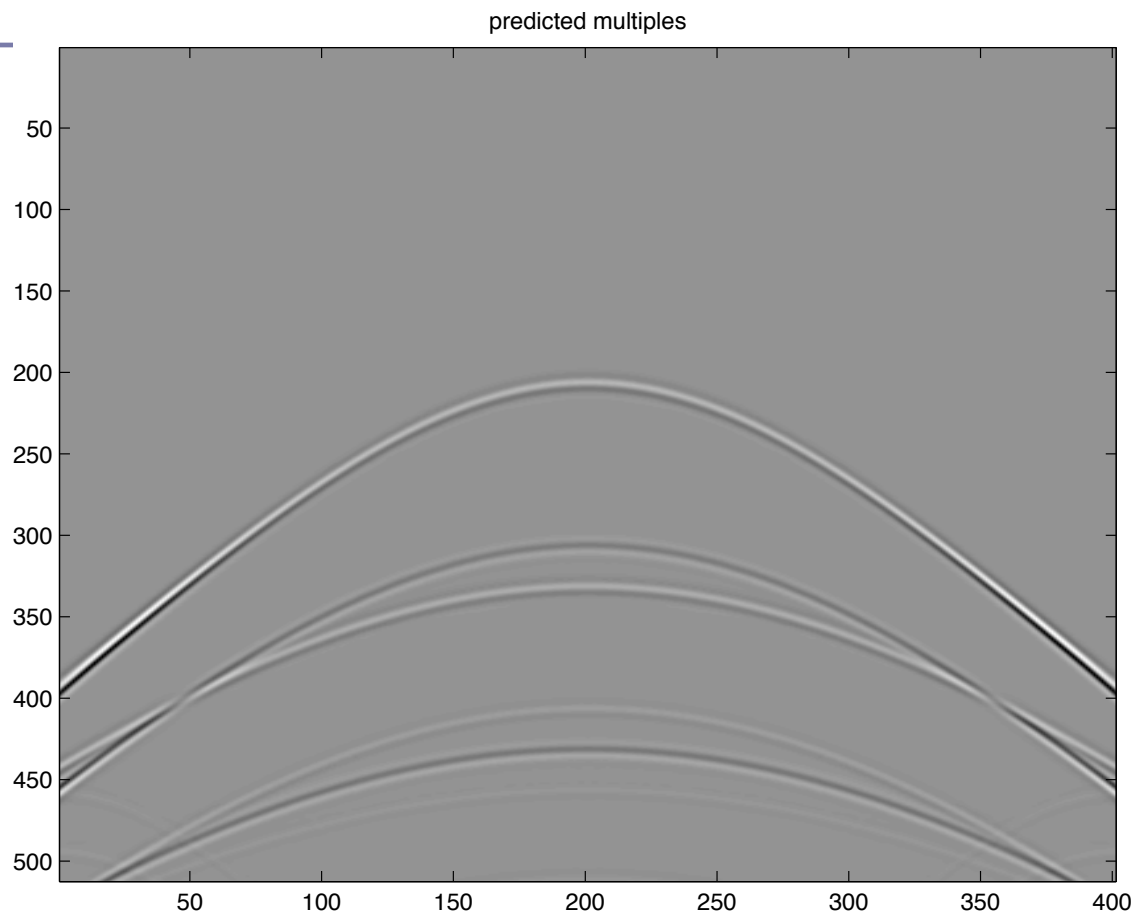
Can we use sparsity arguments?

Total data

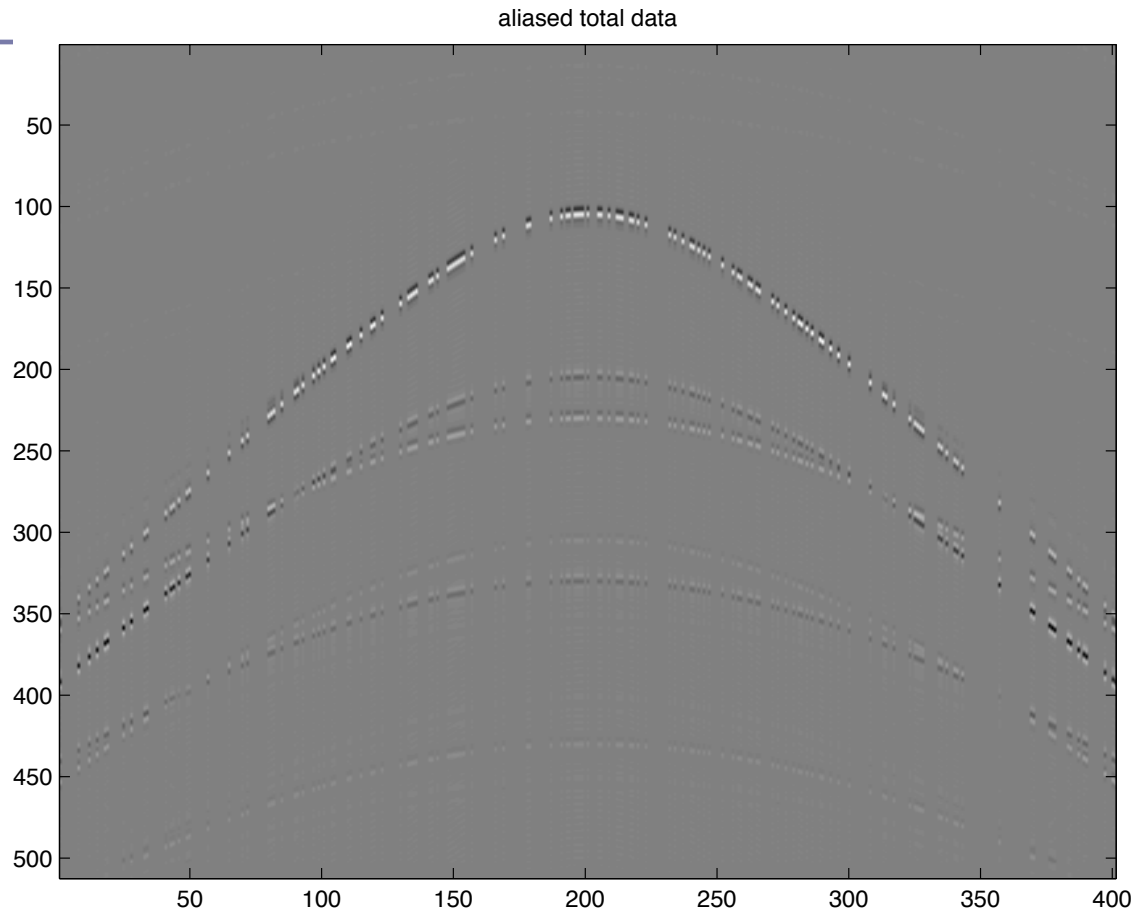
complete total data



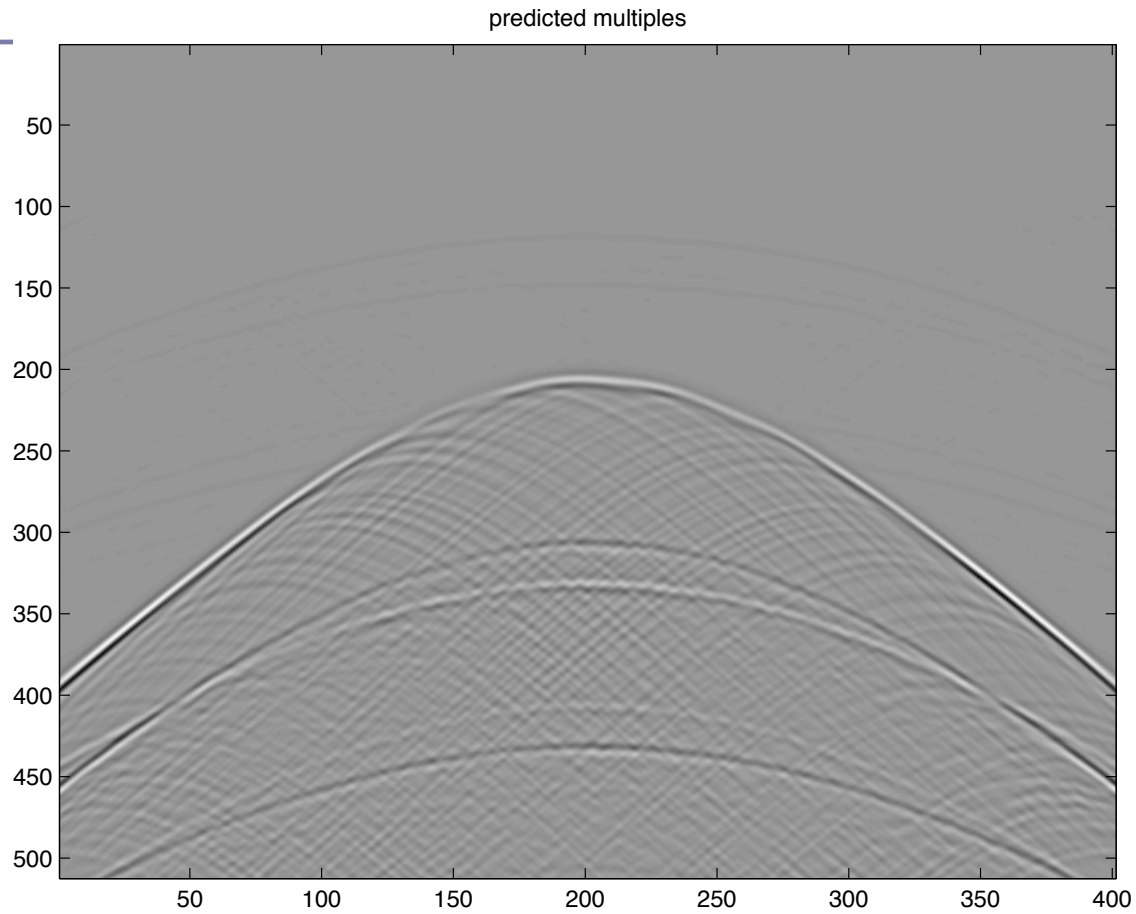
SMRE predicted multiples



Incomplete data



Erroneous prediction



The problem of missing data

Recover data prior to multiple prediction.

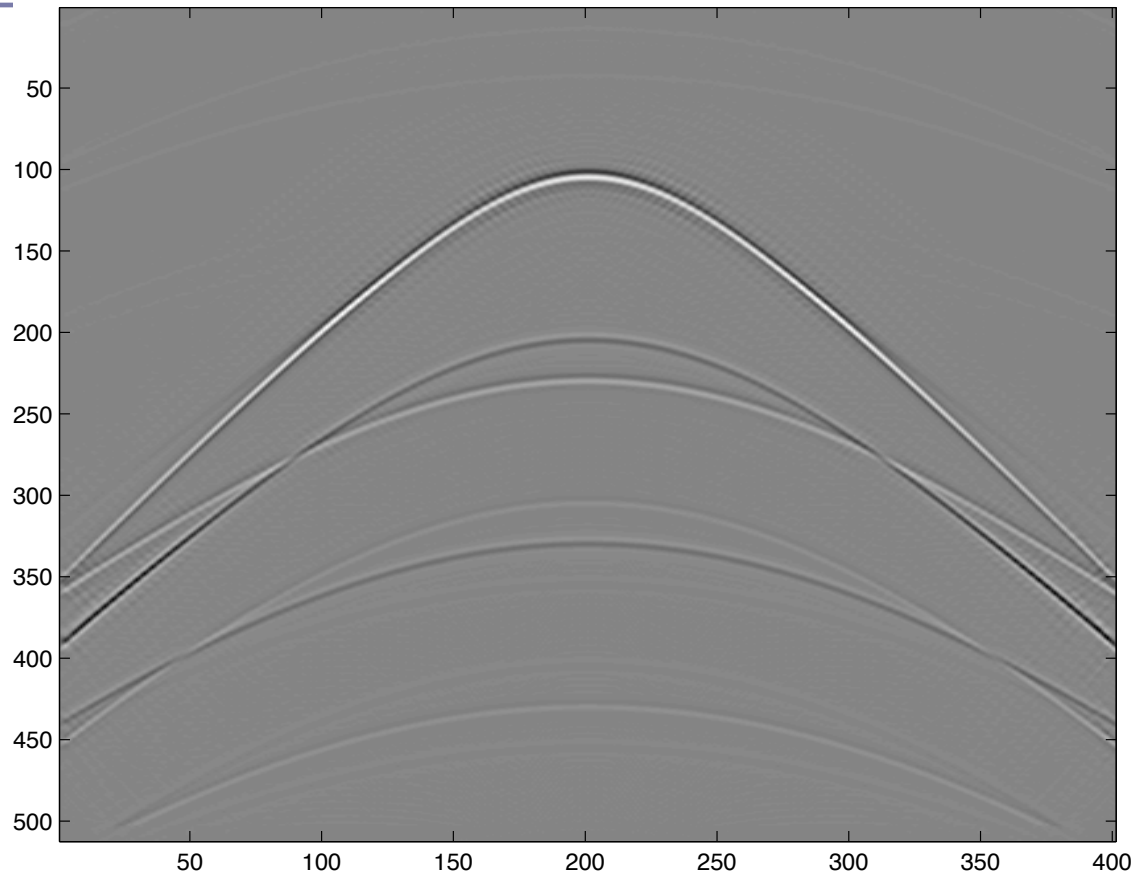
Proceed with SRME prediction.

Will be applied

- higher dimensions
- real data

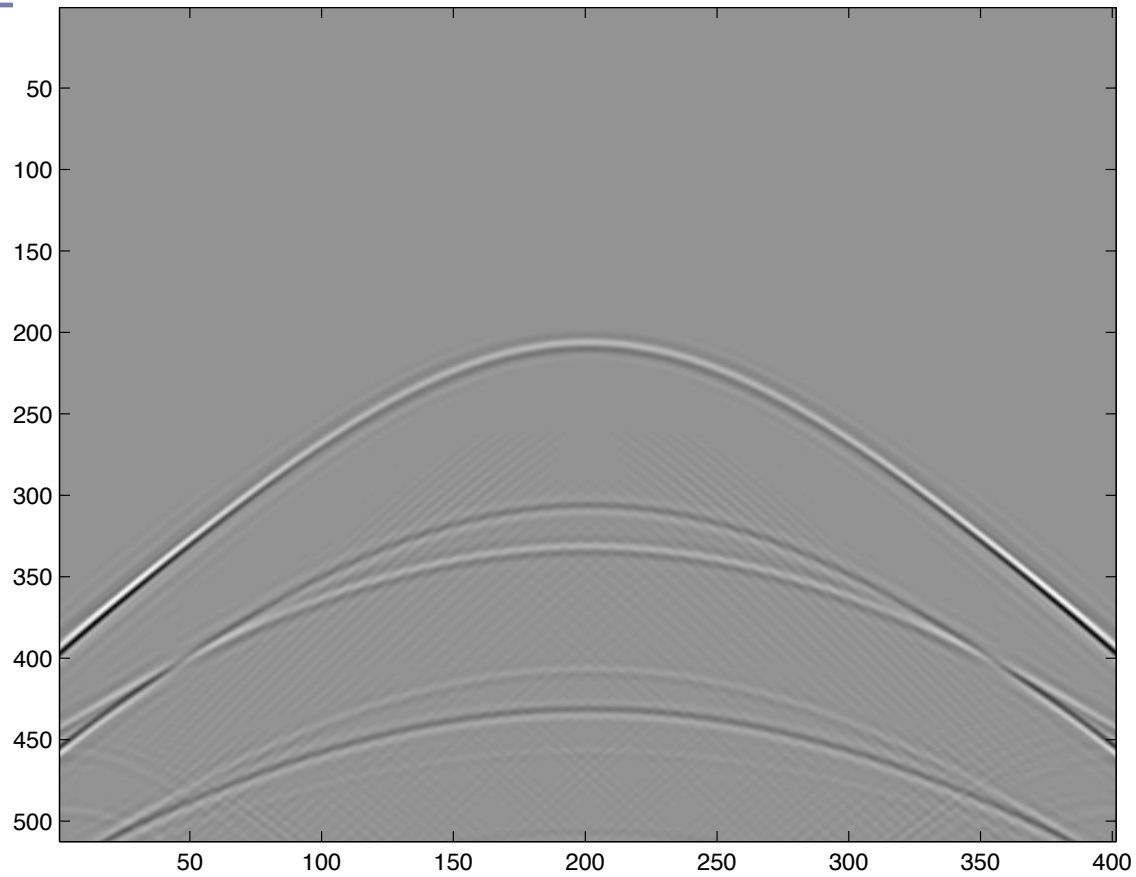
Recovered data

interpolated total data

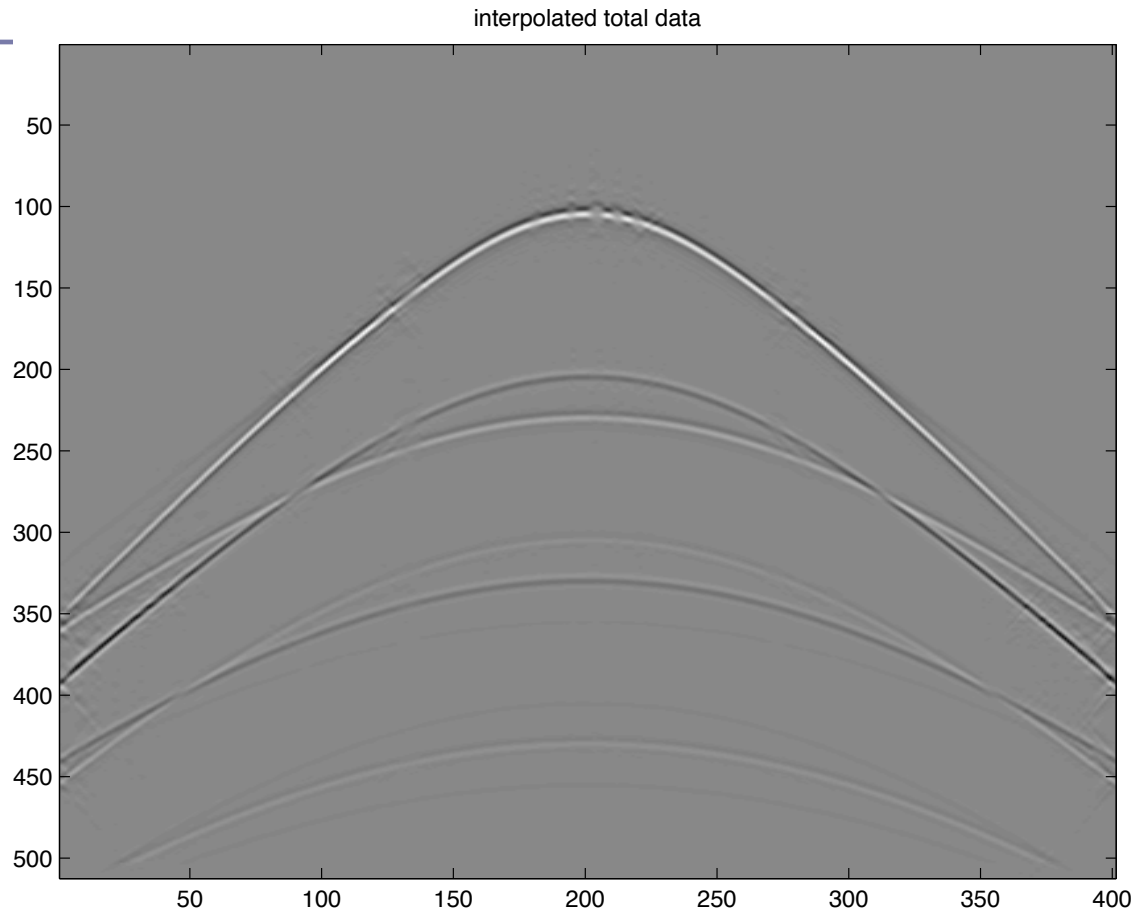


Improved prediction

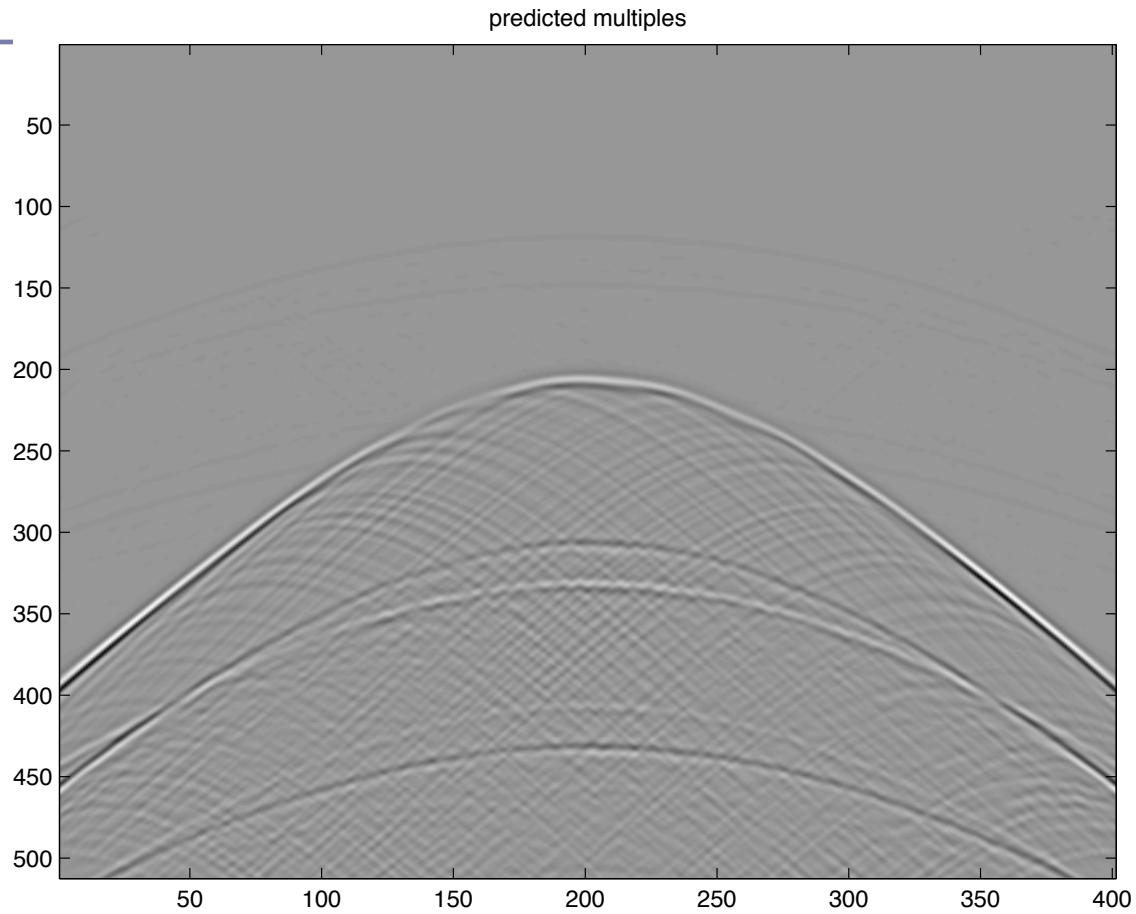
improved multiple predictions



Recovered data

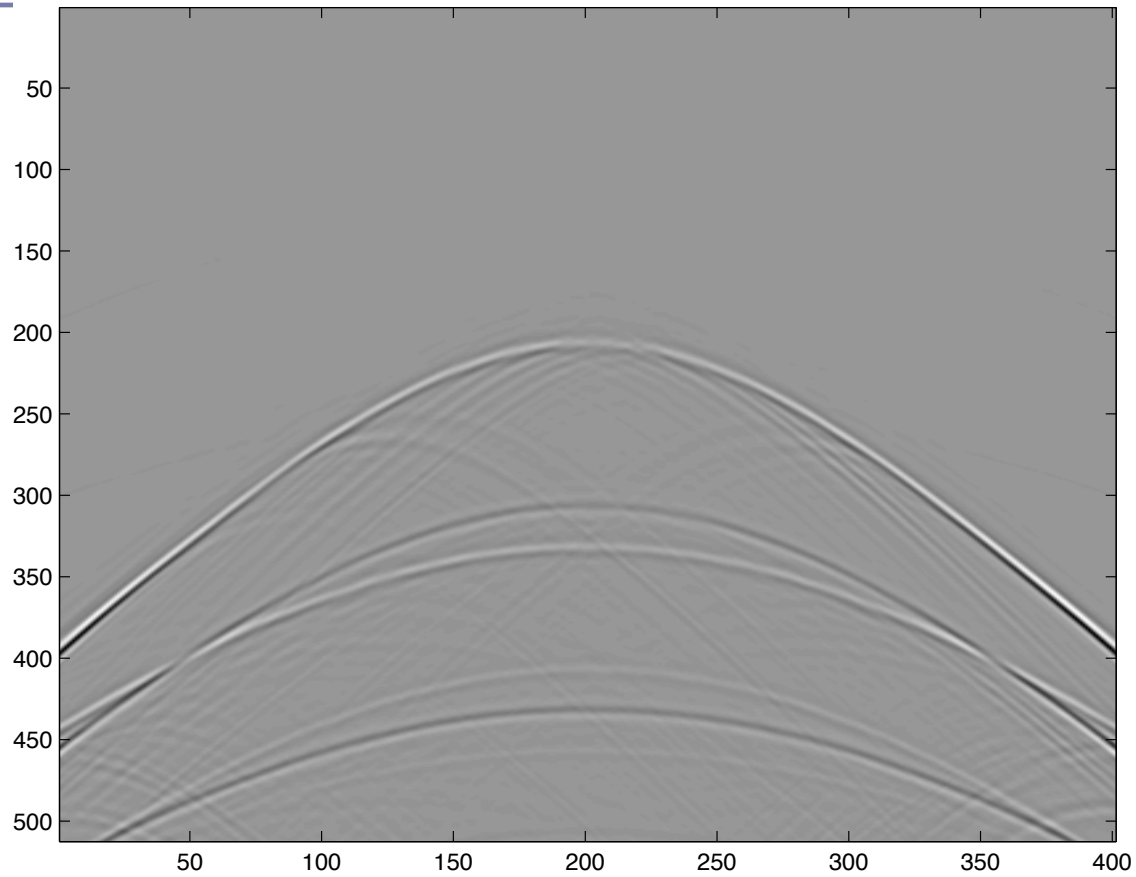


Erroneous prediction



Improved prediction

improved multiple predictions



Data mapping

Wave constituents are related by multidimensional **“cross-convolutions”** mapping:

- primaries to first order multiples; first-order multiples to second order etc.
- spreads the energy & “increases” phase

“cross-correlations” mapping:

- first-order multiples to primaries; second-order multiples to first order etc.
- concentrate the energy and “decreases” phases

Consistent with different terms in the “forward” and “inverse” series, daylight imaging & focal transform.

Primaries 2 multiples references

Primaries into first-order multiples:

$$\Delta p \mapsto m^1 = (\Delta P \mathcal{A} *_{t,x} \Delta p)$$

First-order multiples into primaries:

$$m^1 \mapsto \Delta p = (\Delta P \mathcal{A} \otimes_{t,x} \Delta p)$$

with the acquisition matrix

$$\mathcal{A} = \left(\mathcal{S}^\dagger \mathbf{R} \mathcal{D}^\dagger \right)$$

**“inverting” for source and receiver wavelet
wavelets geometry and surface reflectivity.**

Primaries 2 multiples

Multiple predictions need to be “deblurred”.

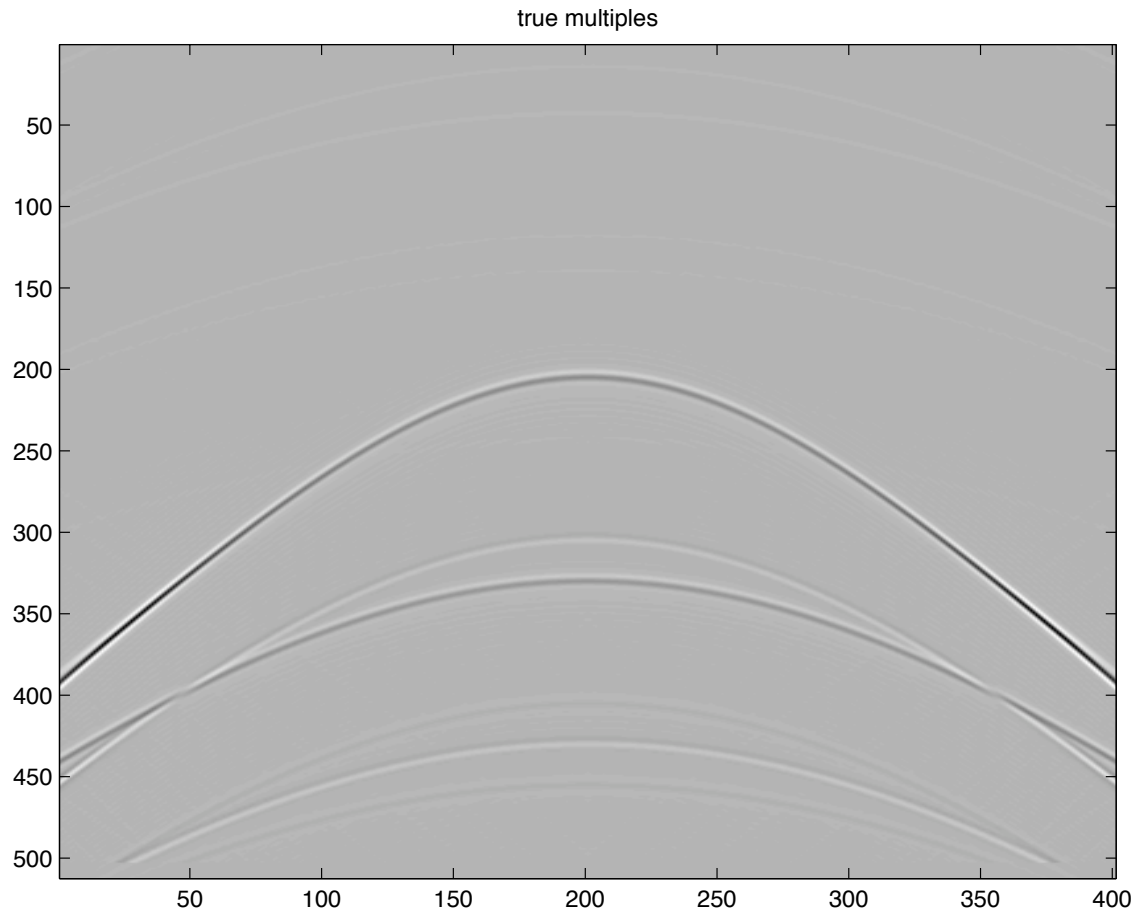
Alternative formulation:

$$\begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{subject to } \mathbf{A}\mathbf{x} = \mathbf{y} \\ \mathbf{A} := \mathbf{\Delta P} \otimes \mathbf{S}^H & \text{(acquisition operator)} \\ \tilde{\mathbf{m}}^1 = \mathbf{S}^H \tilde{\mathbf{x}}. \end{cases}$$

- find the sparsest set of coefficients that *cross-correlated* with the primaries yield the primaries \mathbf{y}
- **no** acquisition operator necessary (tentative)
- acquisition operator is inverted intrinsically

True multiples

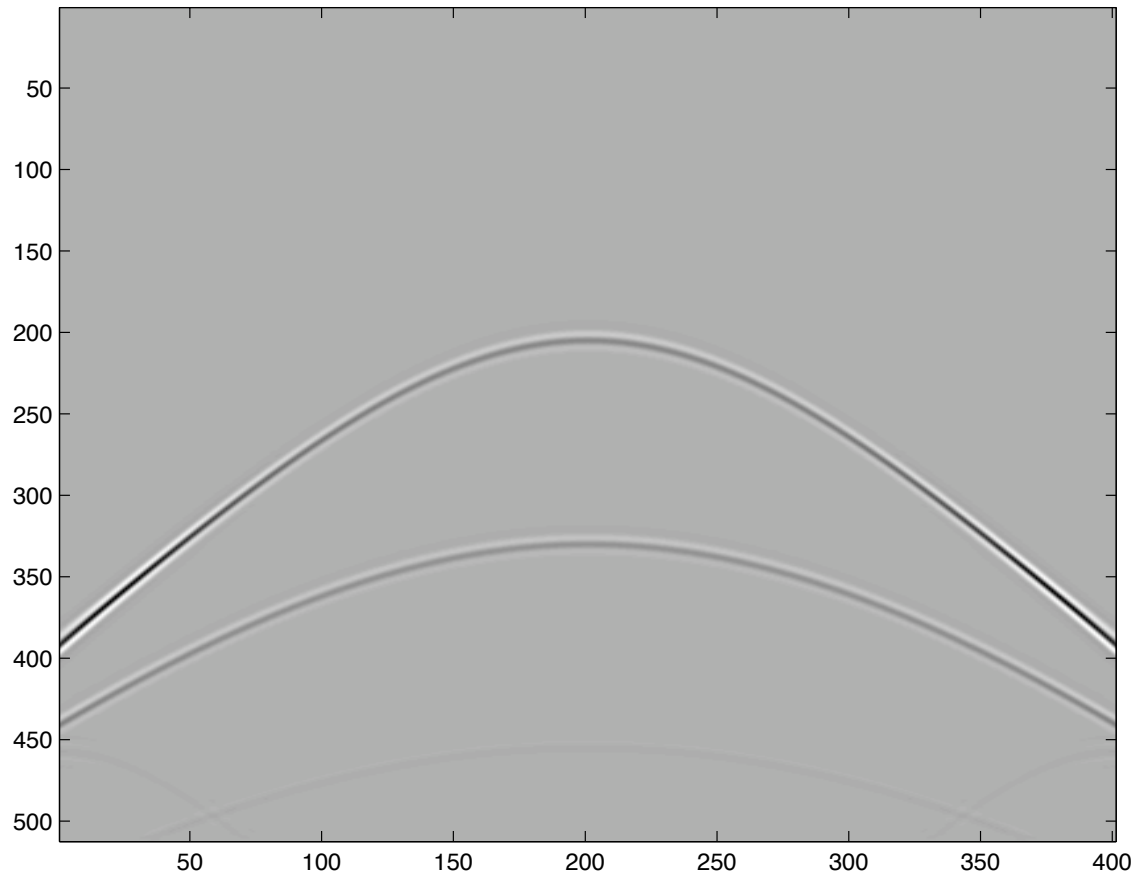
[surface + internal]



Mapped multiples

[surface]

mapped multiples

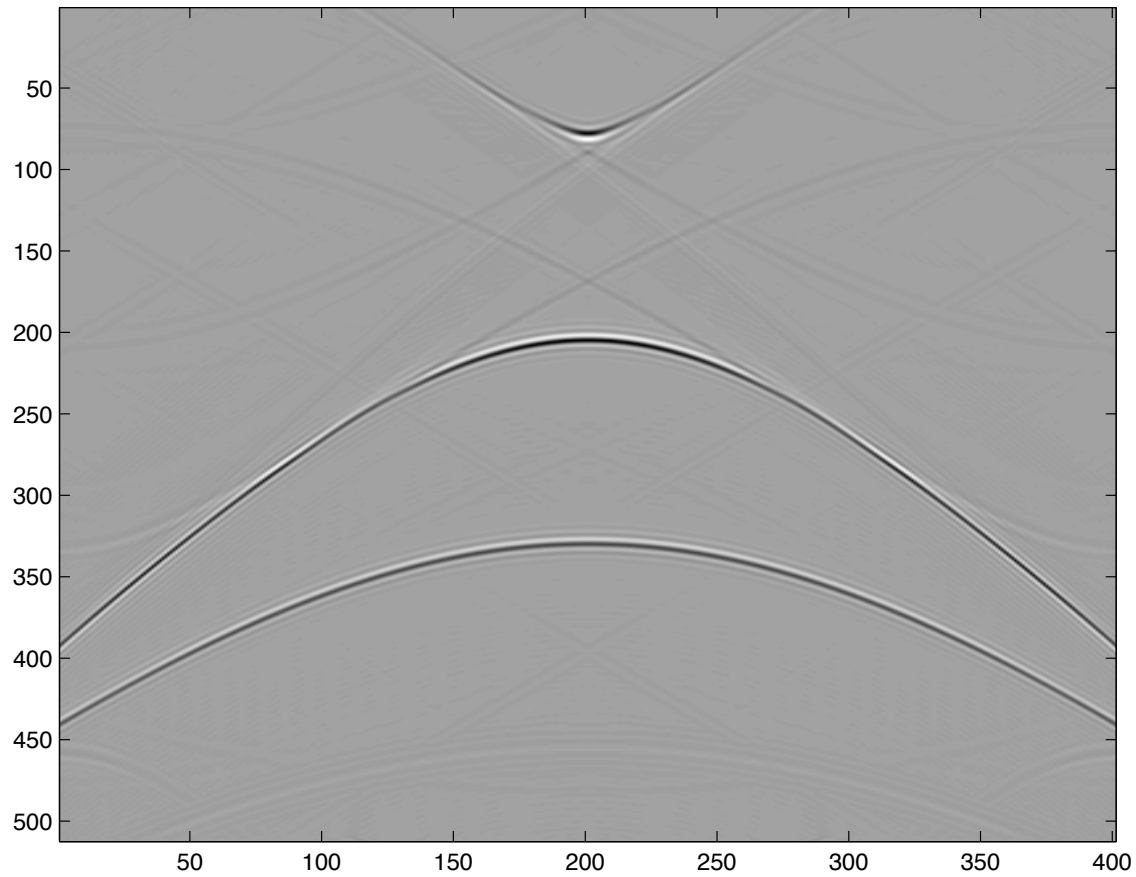


$$\mathbf{M}^1 = (\Delta \mathbf{P} \mathcal{A} *_{t,x} \Delta \mathbf{P})$$

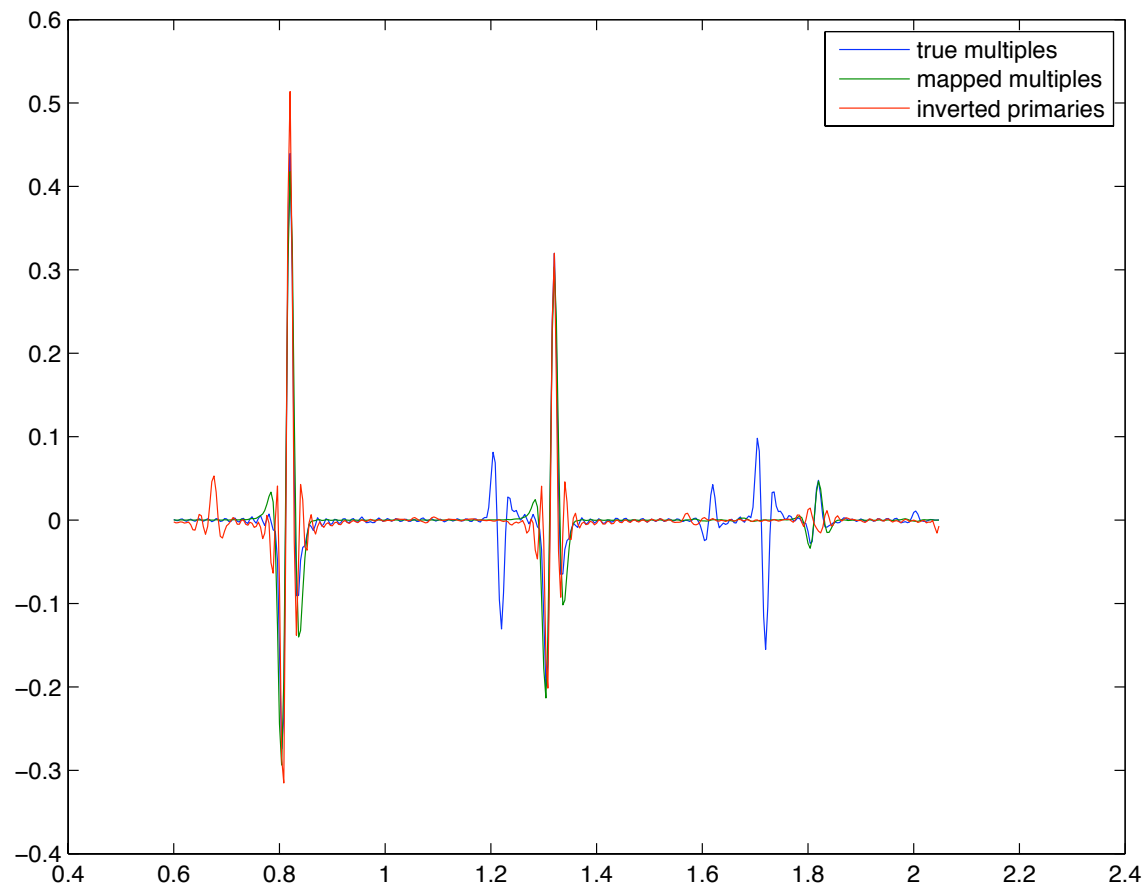
Inverted multiples

[surface]

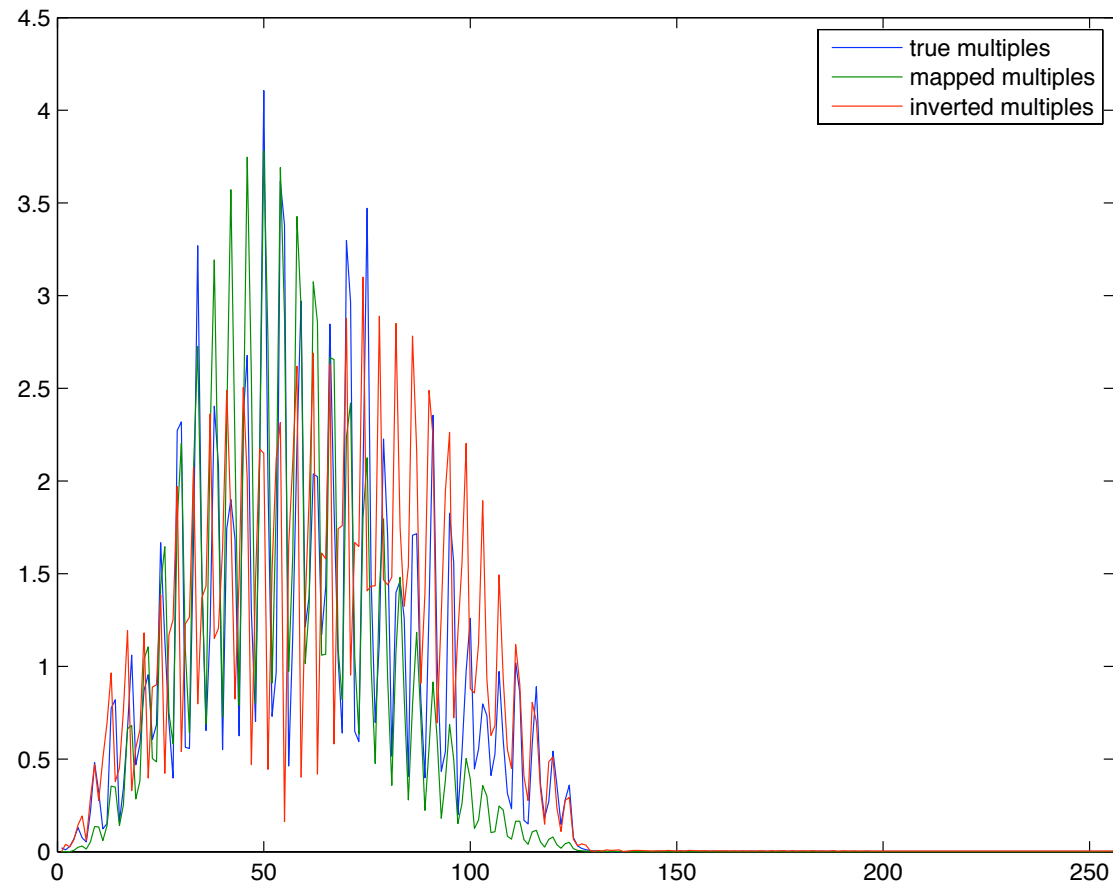
inverted multiples



Mapped vs inverted



Mapped vs inverted



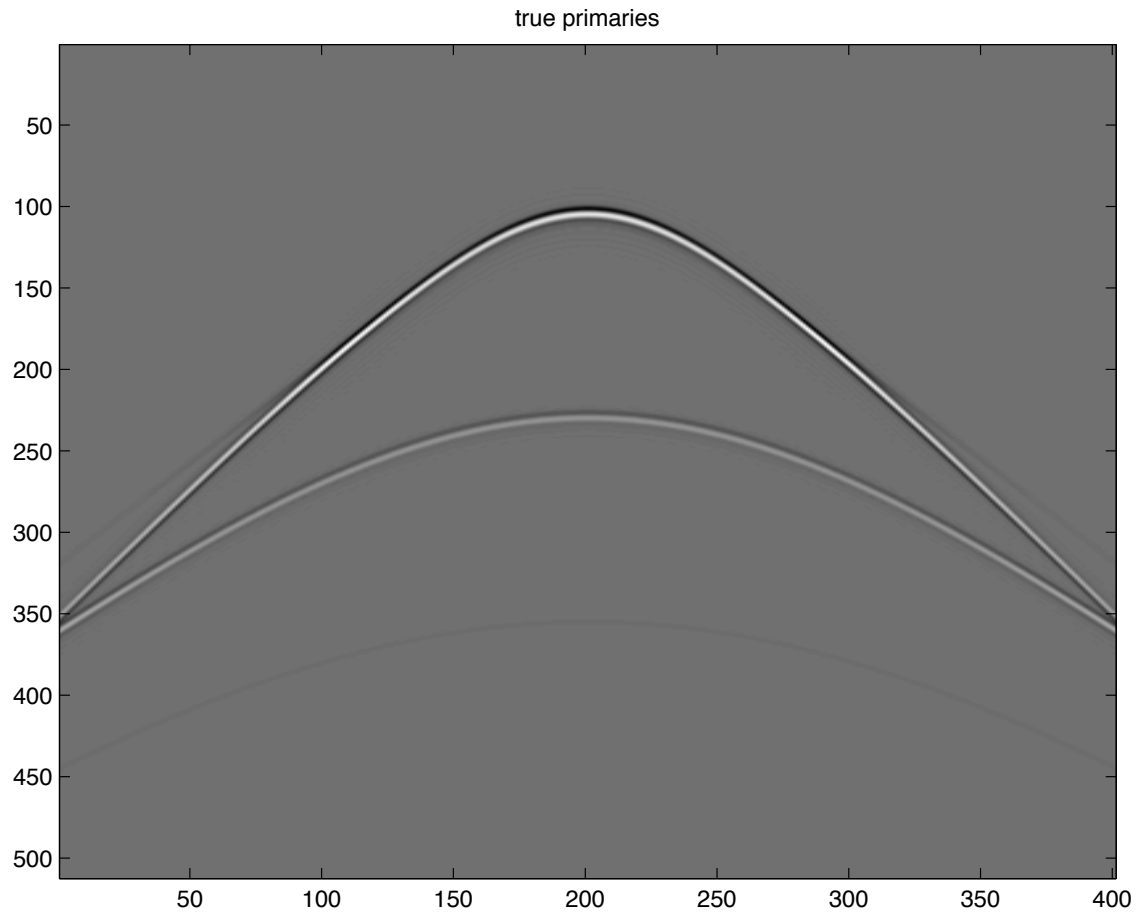
Multiples 2 primaries

Primary predictions need to be “deblurred”.
Alternative formulation:

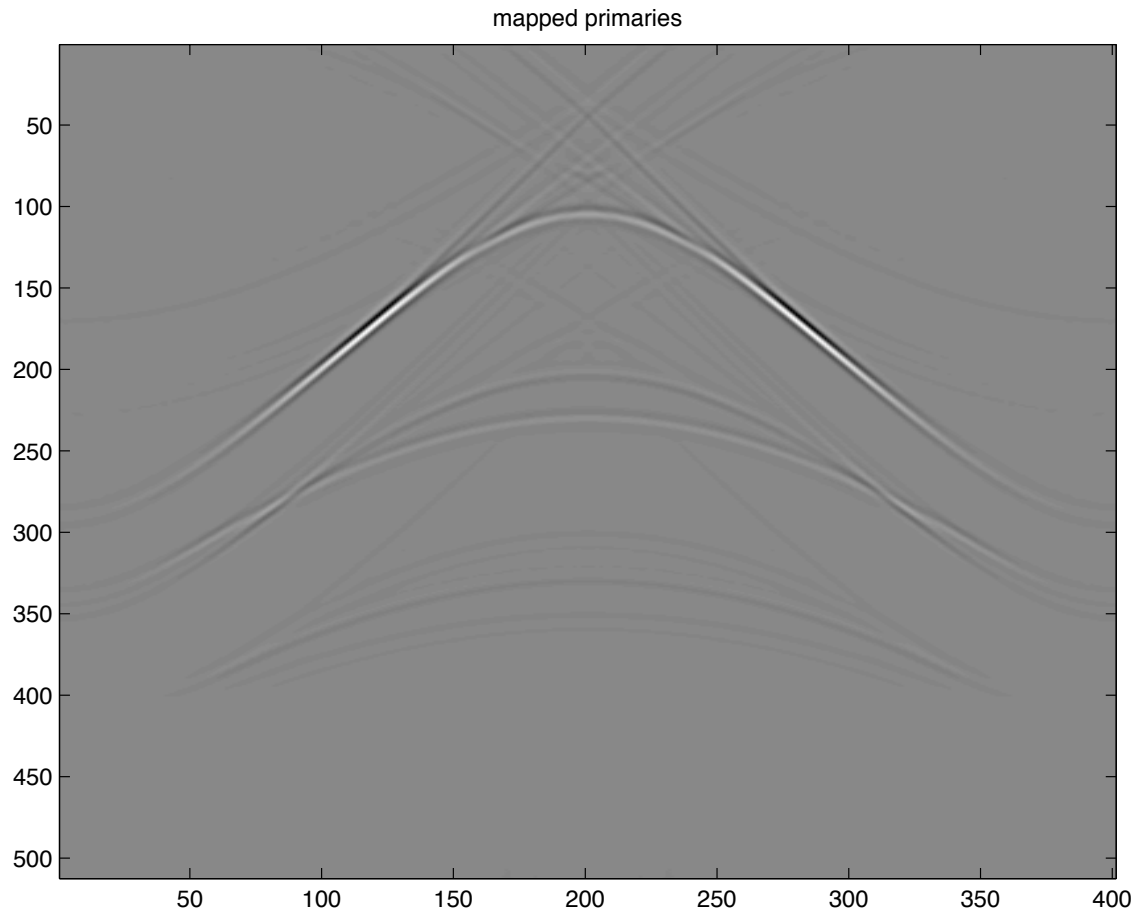
$$\begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{subject to } \mathbf{A}\mathbf{x} = \mathbf{y} \\ \mathbf{A} := \Delta\mathbf{P} * \mathbf{S}^H \\ \tilde{\Delta\mathbf{p}} = \mathbf{S}^H \tilde{\mathbf{x}}. \end{cases}$$

- find the sparsest set of coefficients that cross-convoluted with the primaries yields the multiples \mathbf{y}
- **no** acquisition operator necessary
- acquisition operator is inverted intrinsically
- compare with the focal transform

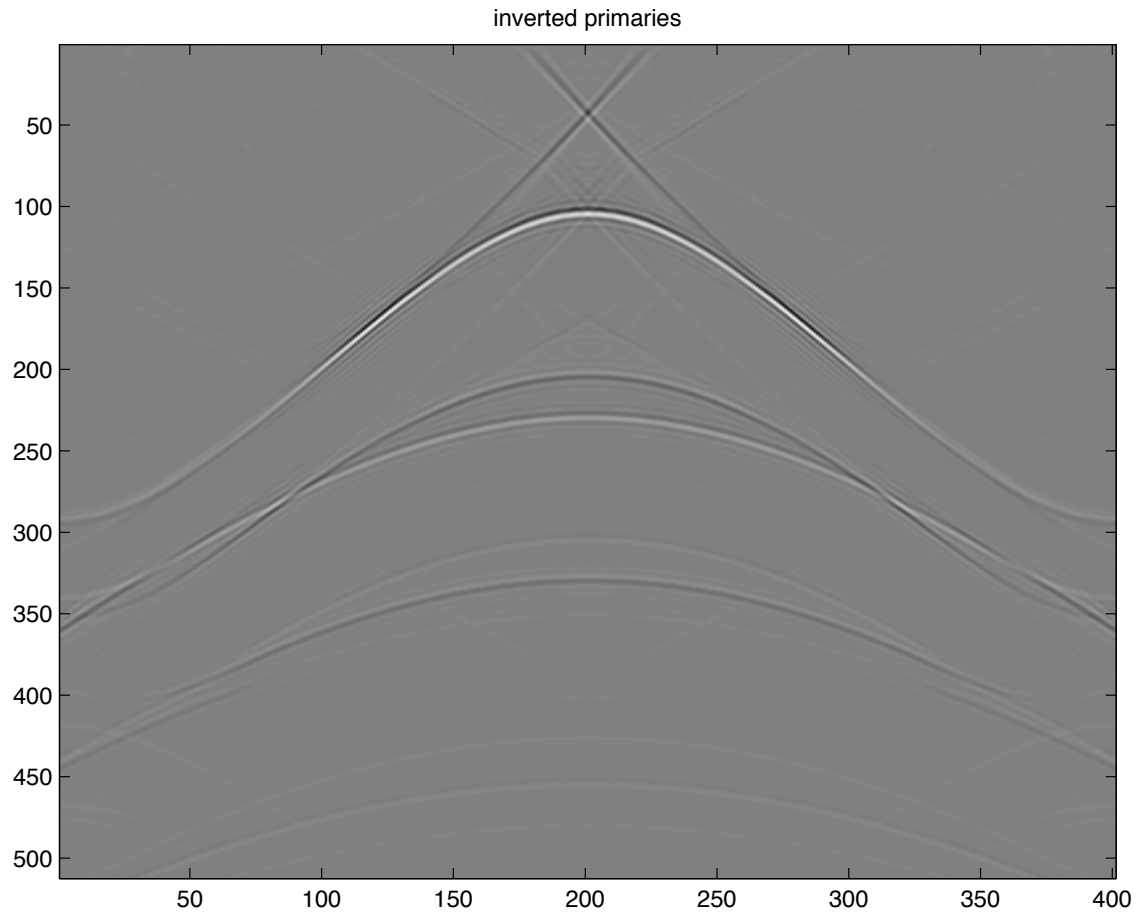
True primaries



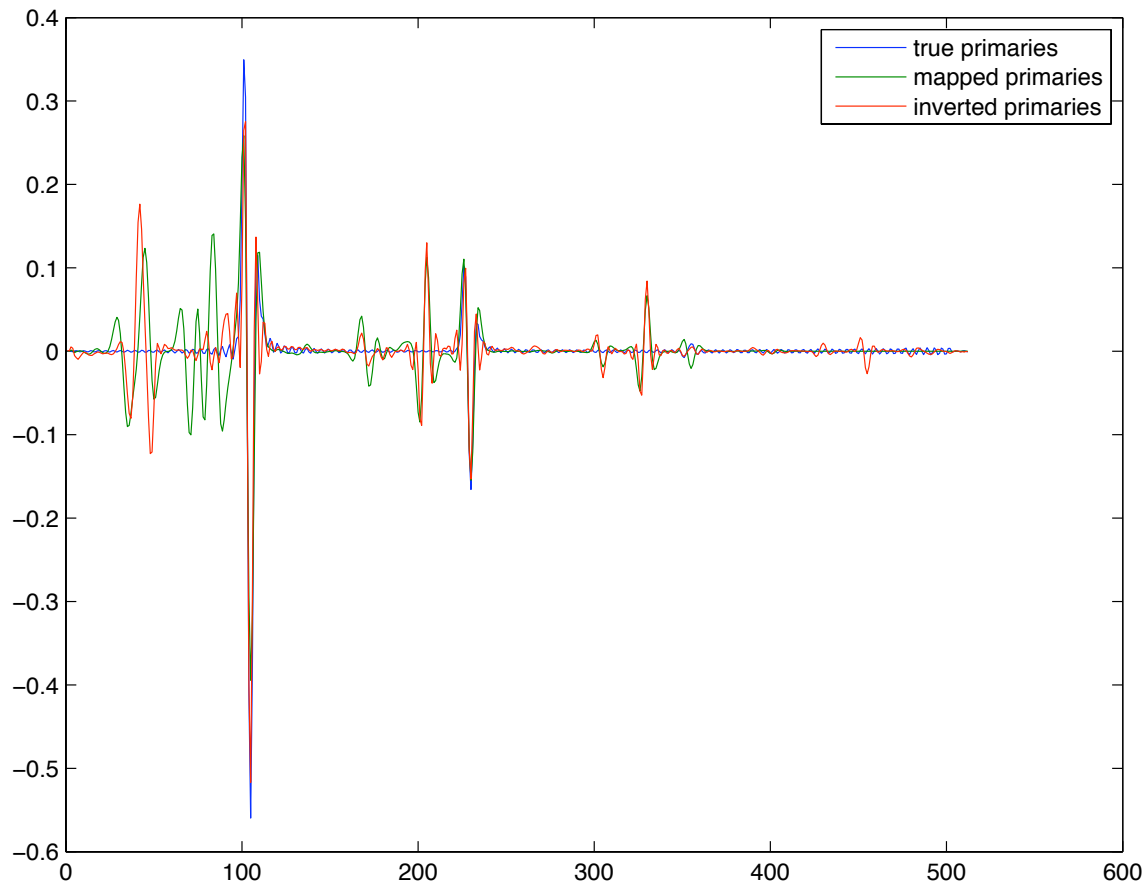
Mapped primaries



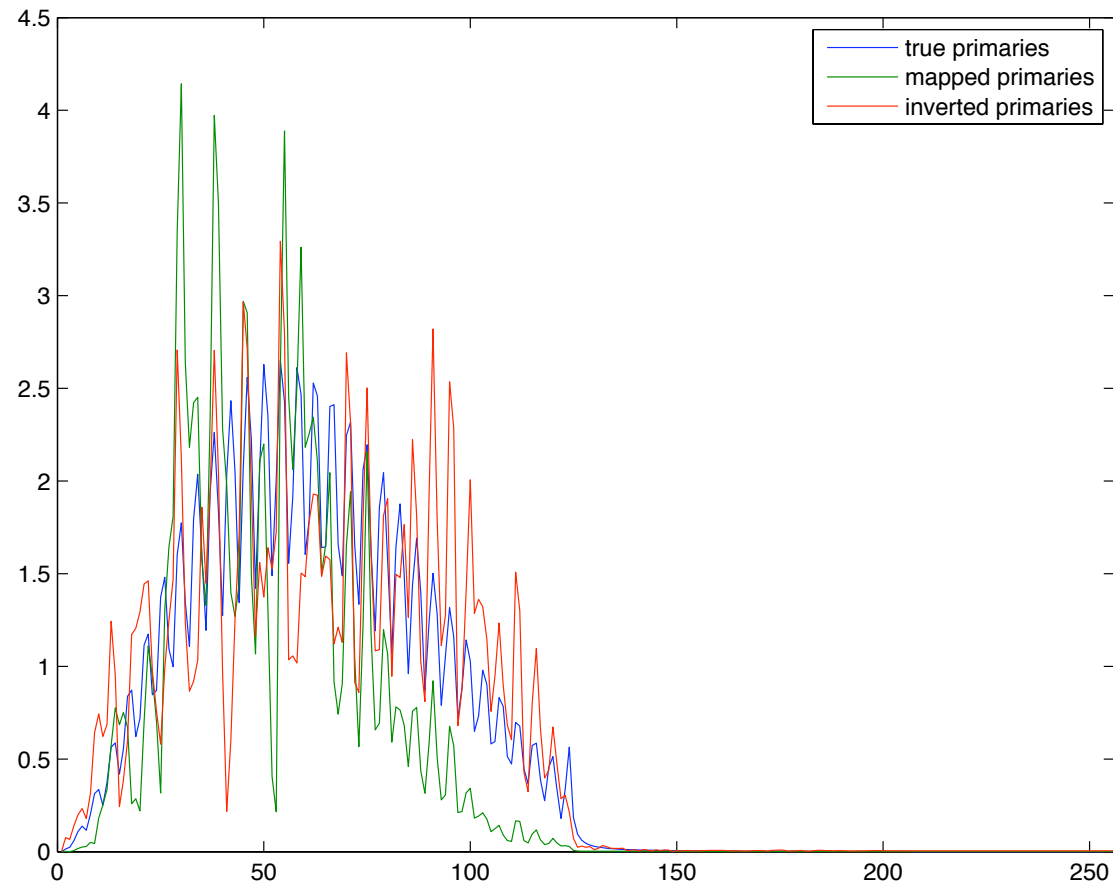
Inverted primaries



Mapped vs inverted



Mapped vs inverted



Observations

Primaries can be mapped to multiples and *vice versa*.

Formulation with sparsity constraints

- does not require info on acquisition
- preserves frequency content

Primaries 2 multiples *spreads* energy

Multiples 2 primaries *concentrates* energy

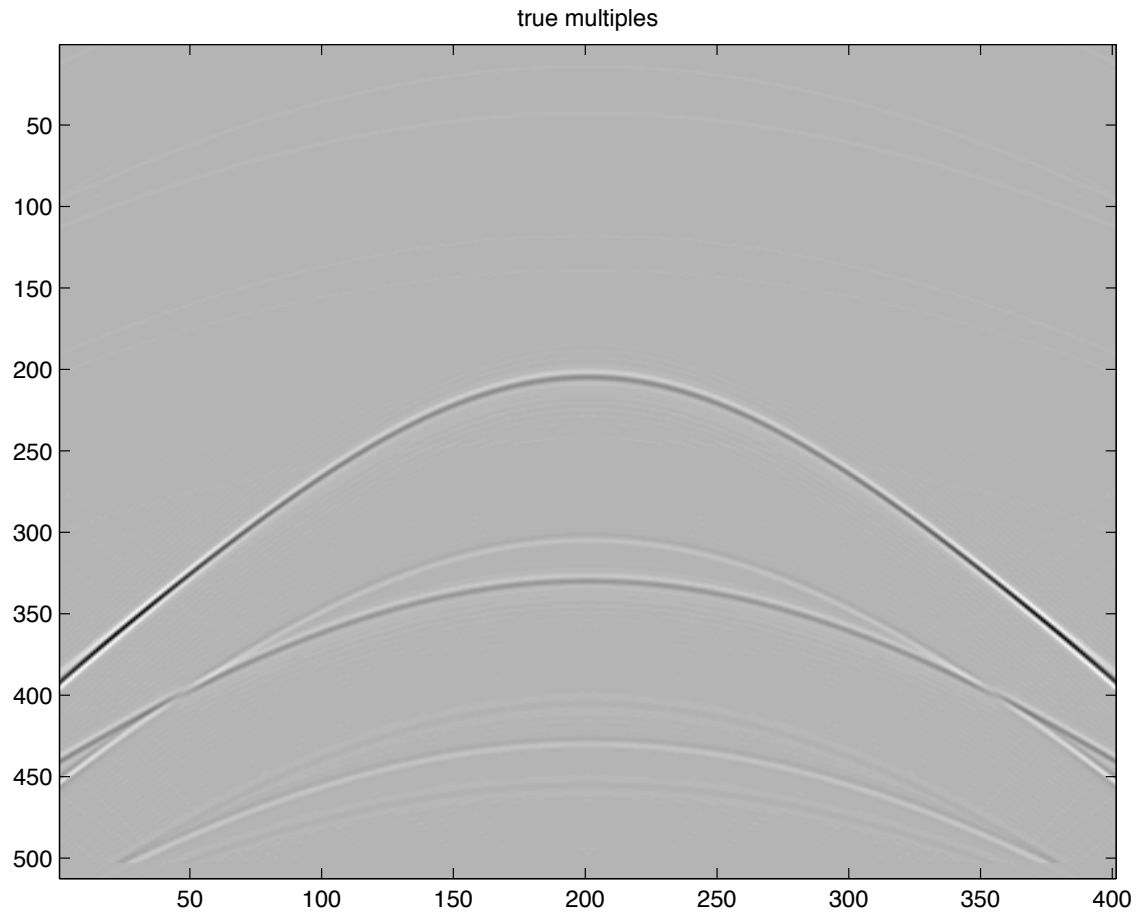
- Plots are *modulus* signs
- Needed a Hilbert transform + 3 sample shift

Same can be done with total data

Focussing can be used to do interpolation

True multiples

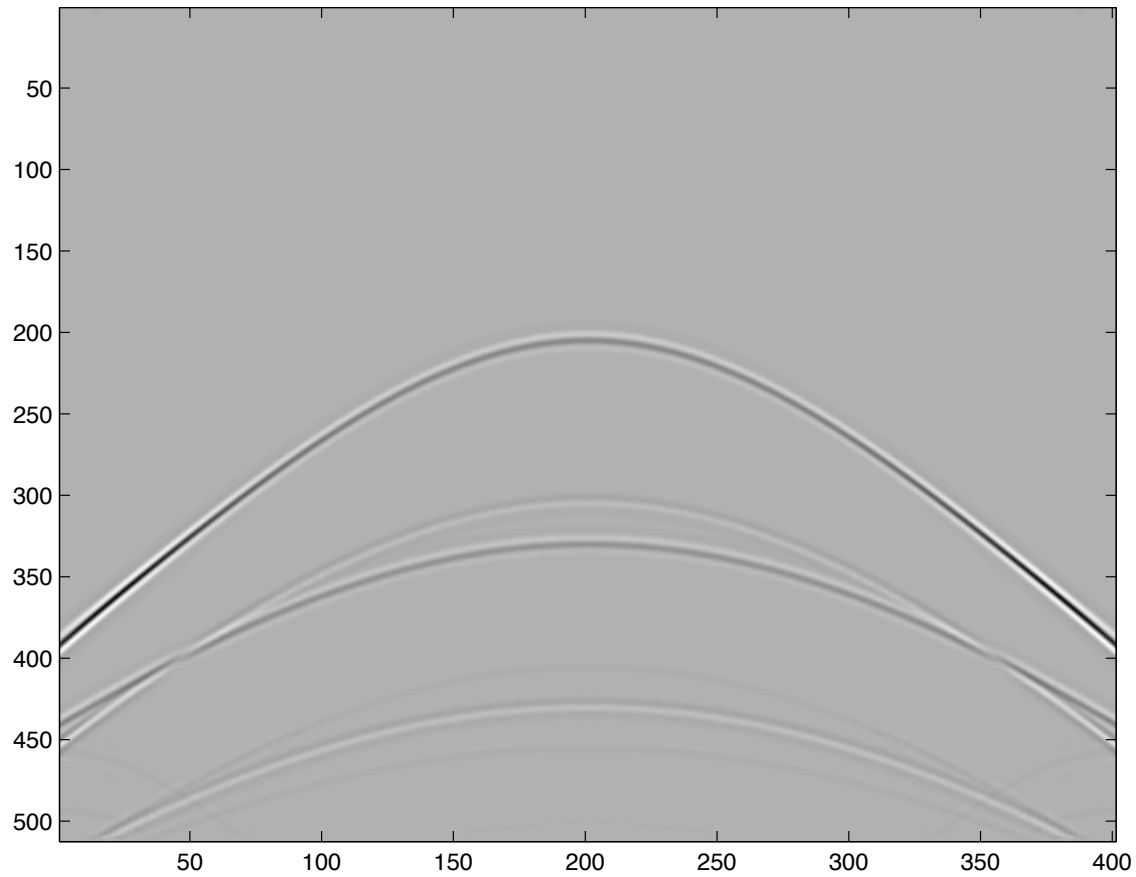
[surface + internal]



Mapped multiples

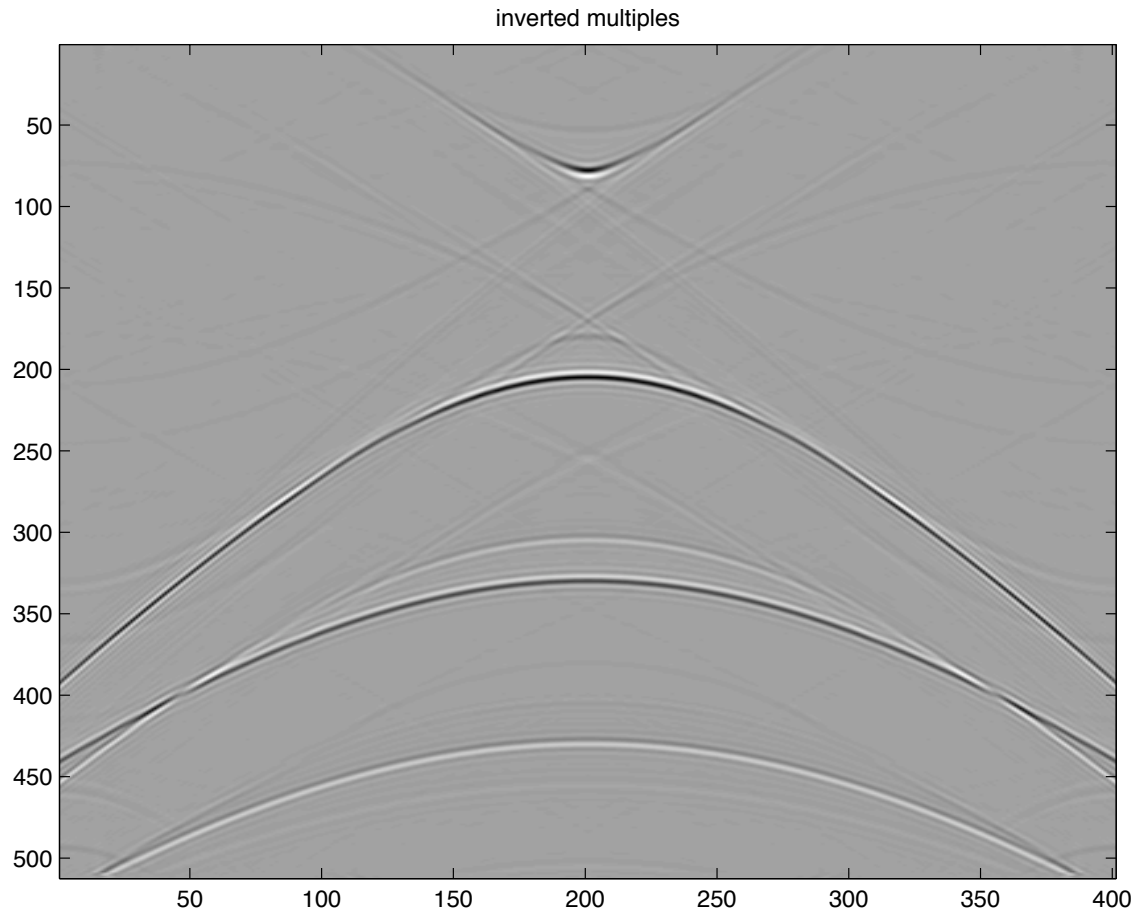
[surface + internal]

mapped multiples

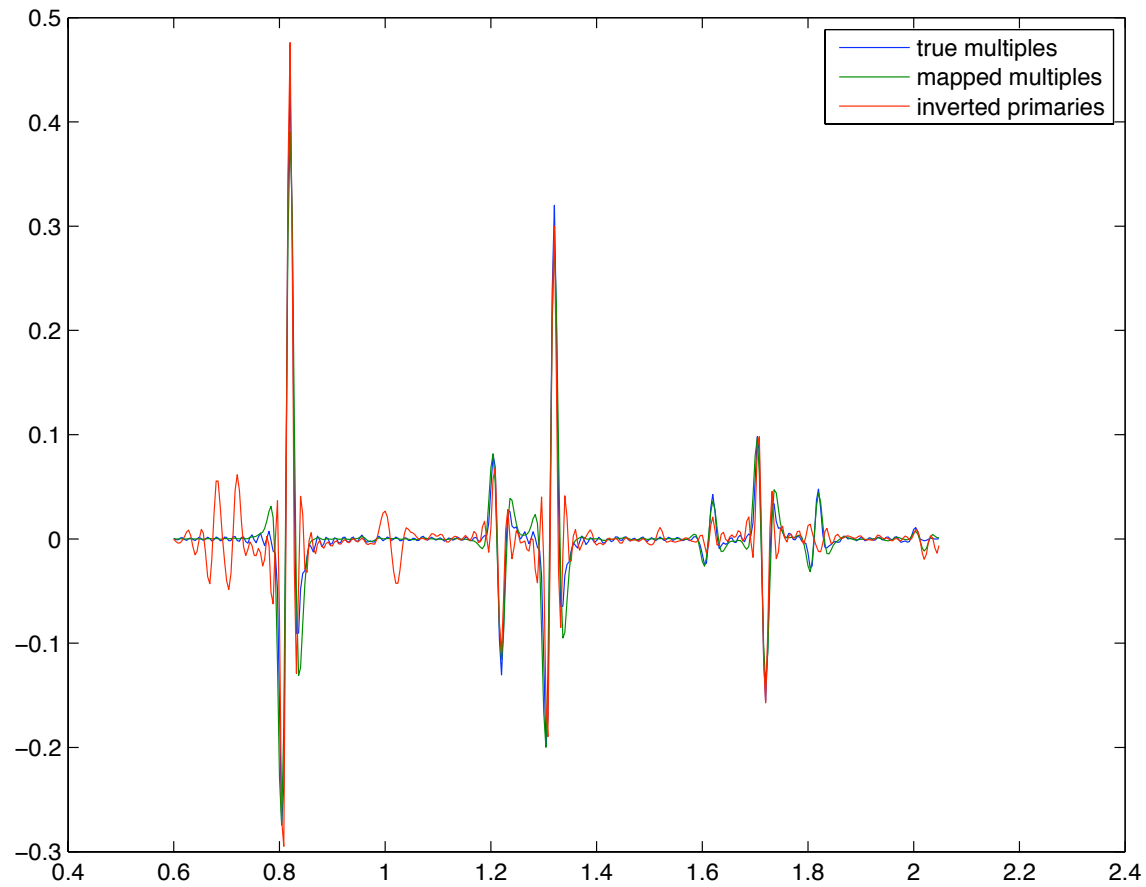


Inverted multiples

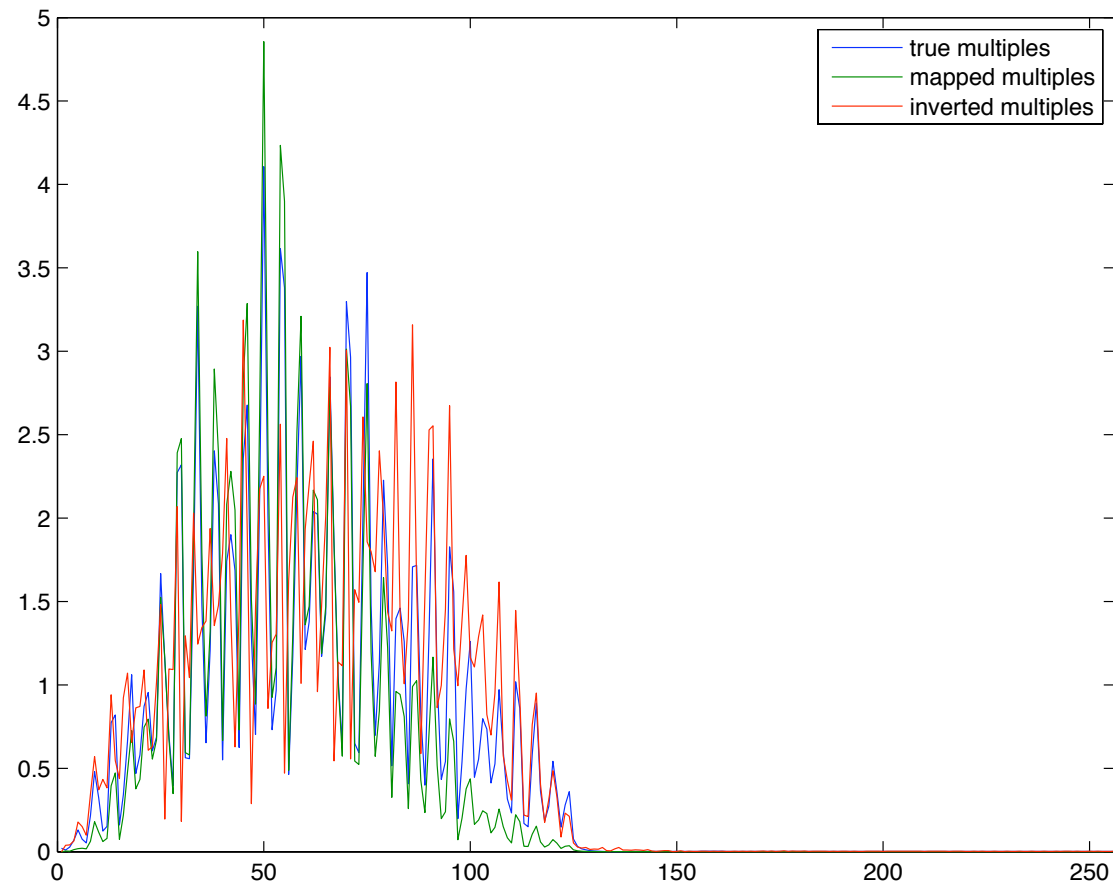
[surface and internal]



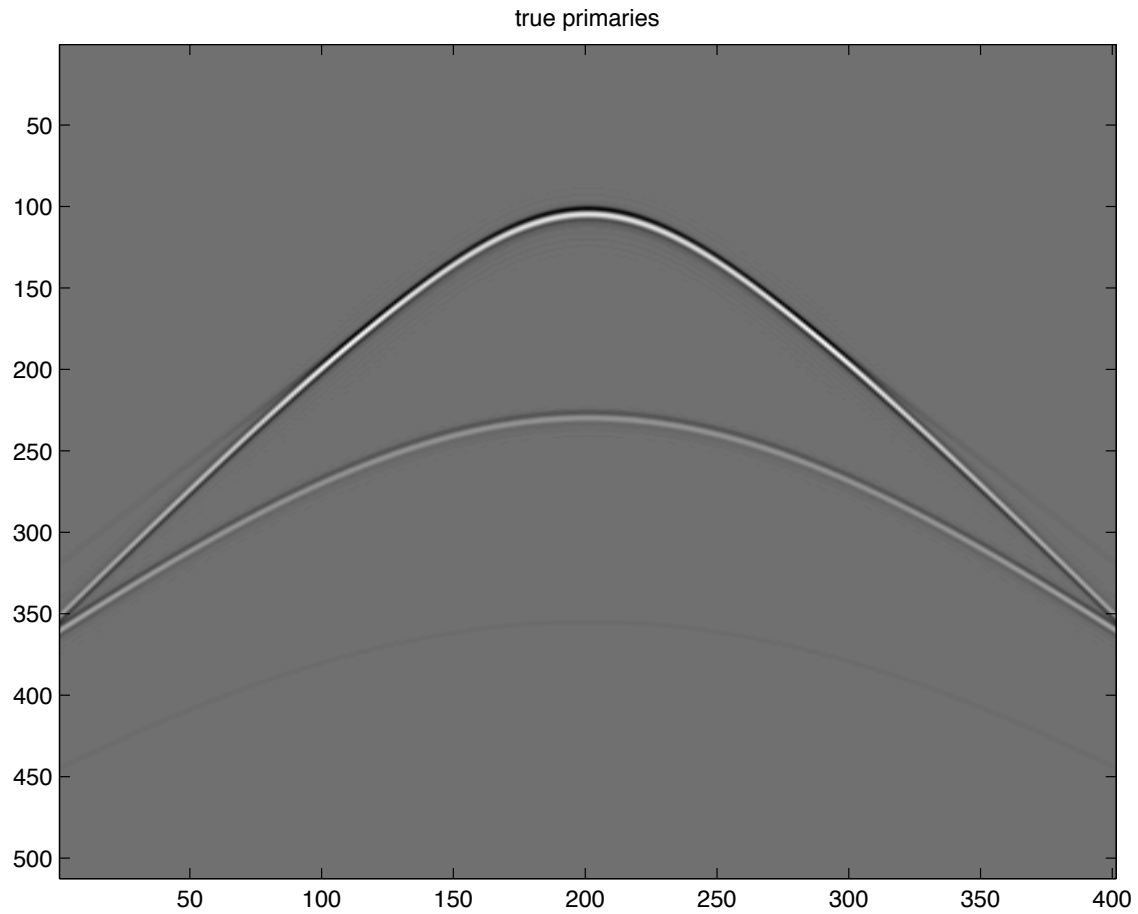
Mapped vs inverted



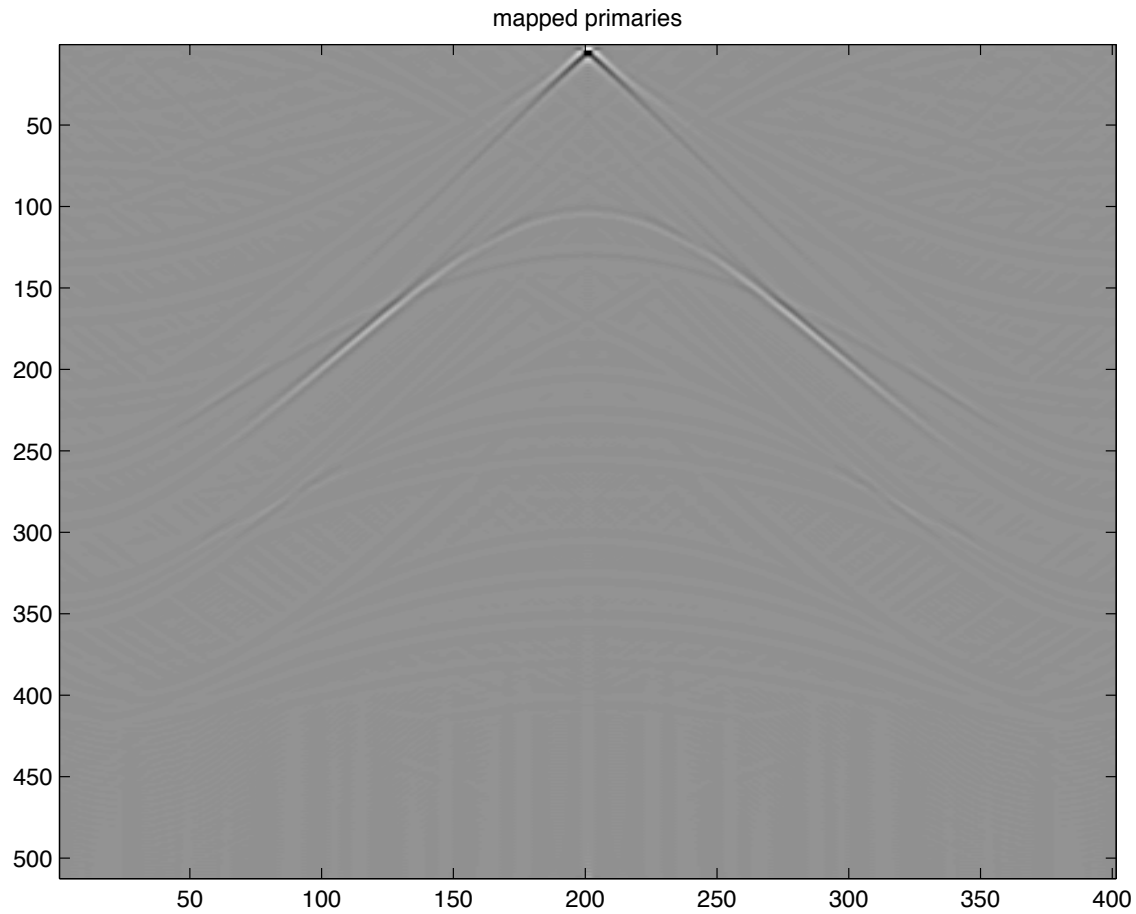
Mapped vs inverted



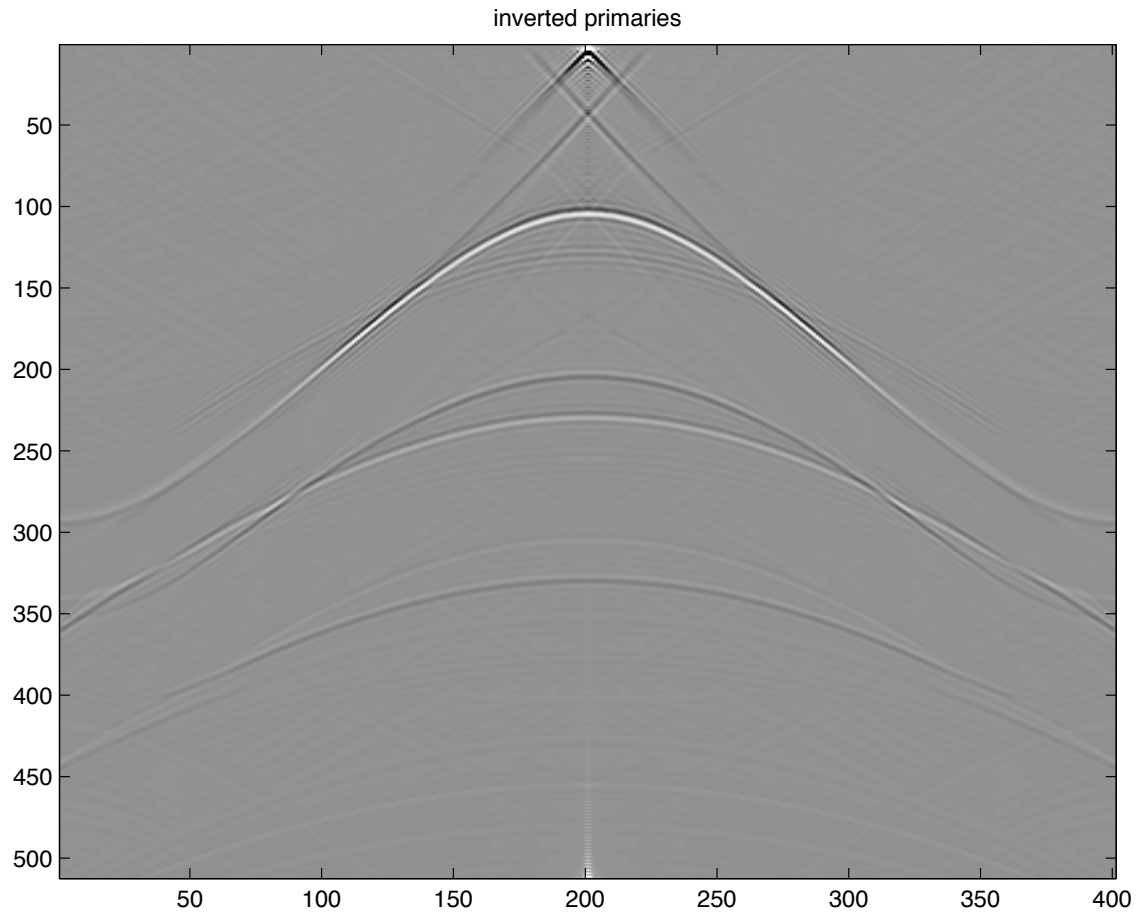
True primaries



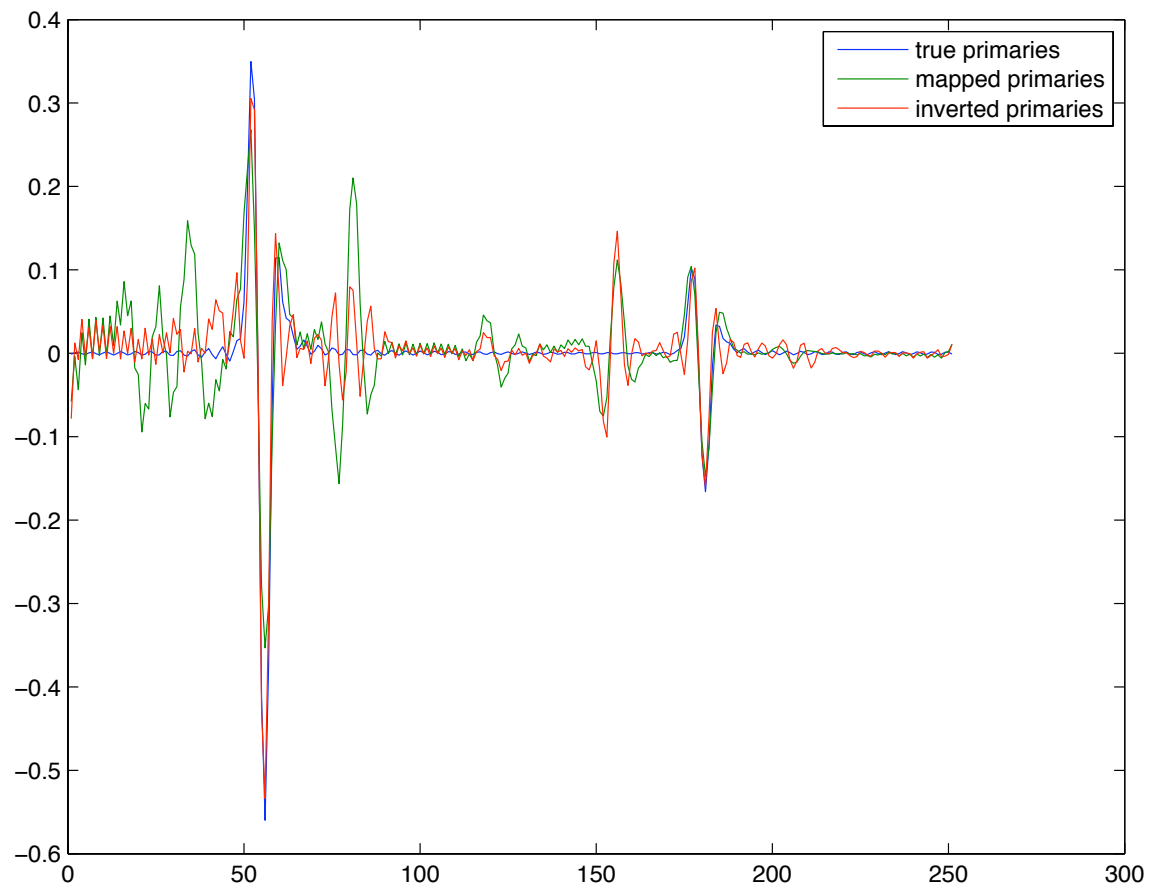
Mapped primaries



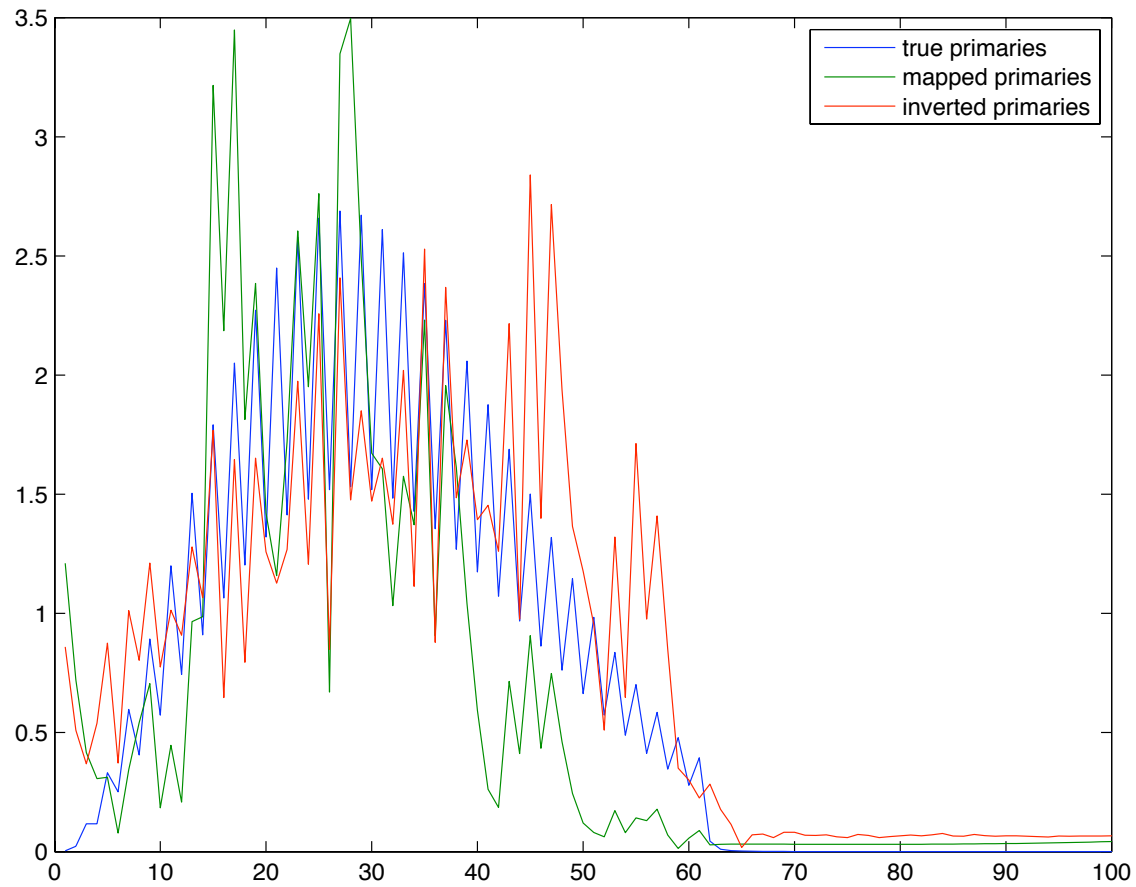
Inverted primaries



Mapped vs inverted



Mapped vs inverted



Recovery by focussing

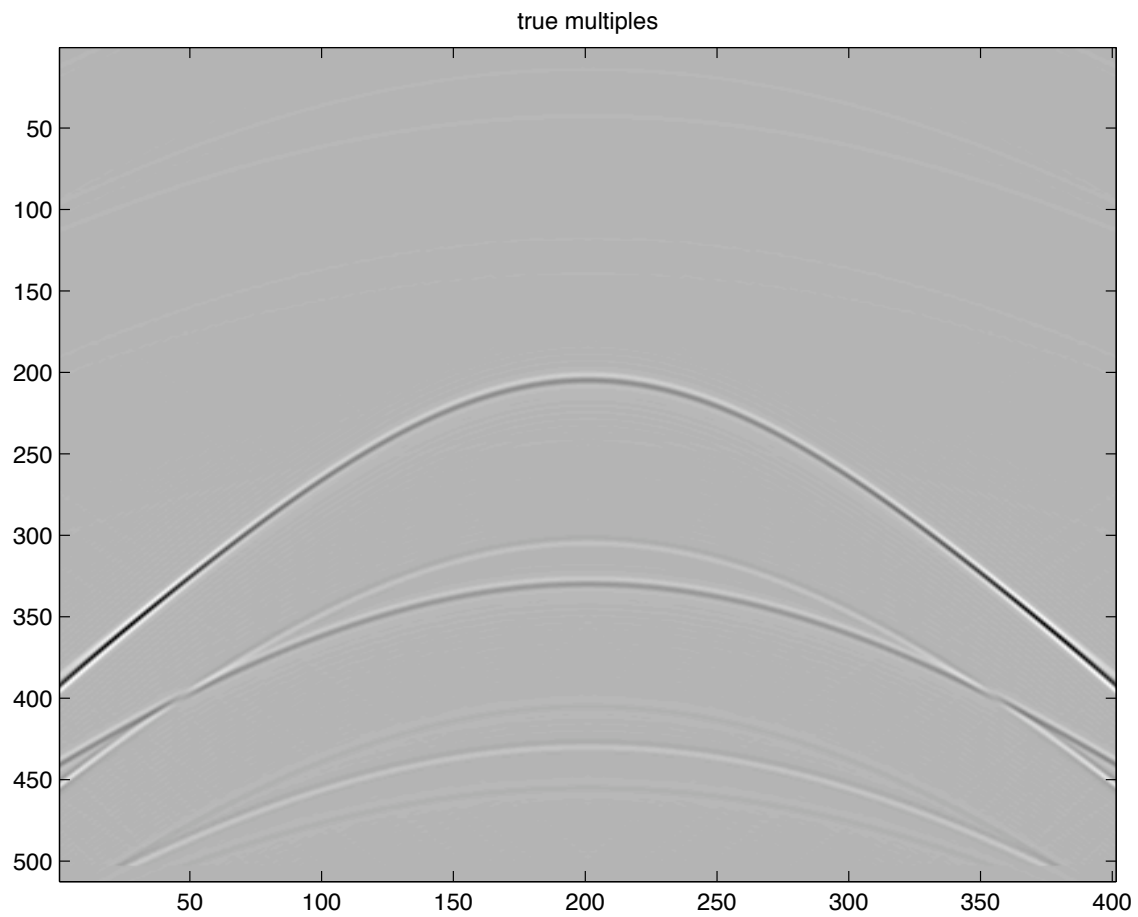
Remember inverting cross-convolution focusses.
Interpolate incomplete multiple energy through

$$\begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{subject to } \mathbf{A}\mathbf{x} = \mathbf{y} \\ \mathbf{A} := \mathbf{RI} \left(\Delta\mathbf{P} * \mathbf{S}^H \right) \\ \tilde{\mathbf{m}}^1 = \mathbf{A}\tilde{\mathbf{x}}, \mathbf{y} = \mathbf{RI}\mathbf{m}^1. \end{cases}$$

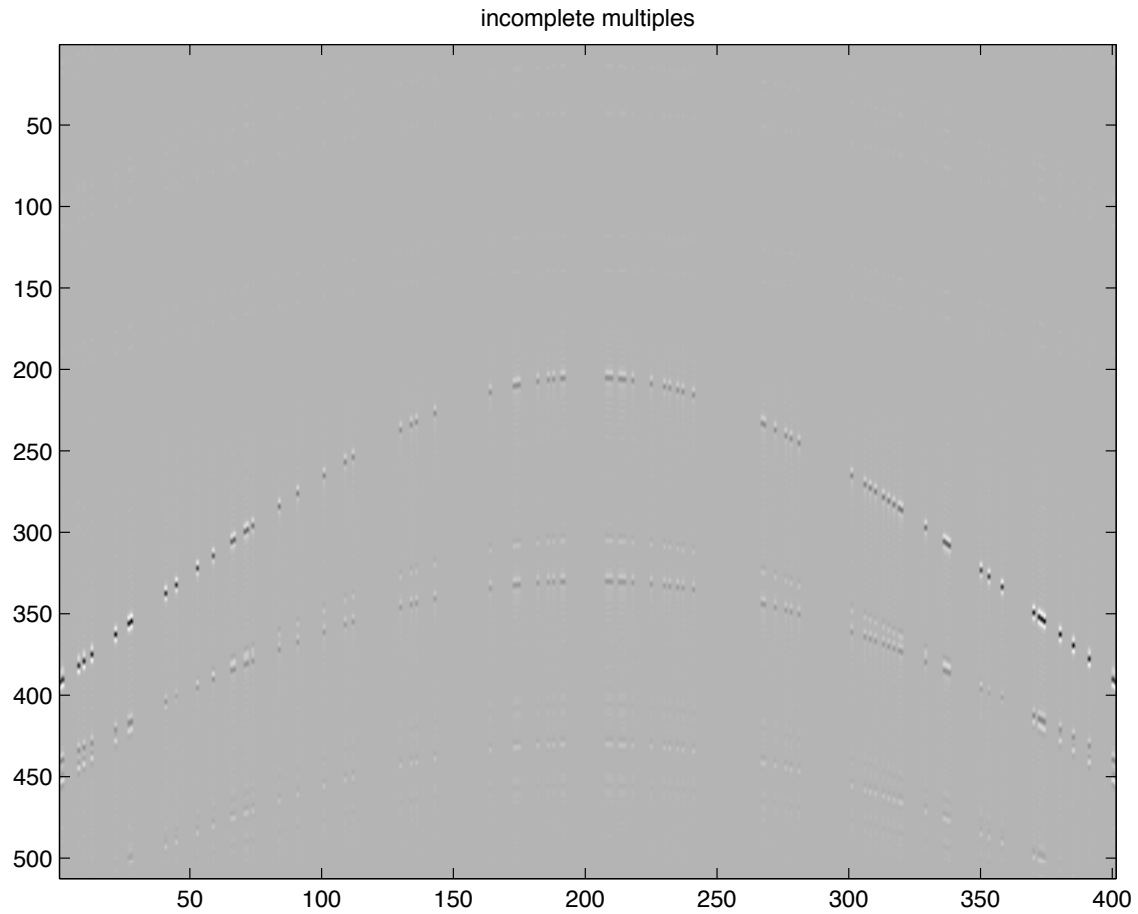
with \mathbf{y} the incomplete multiples.

- \mathbf{R} is the restriction operator
- \mathbf{I} the Dirac measurement matrix
- multiples are recovered

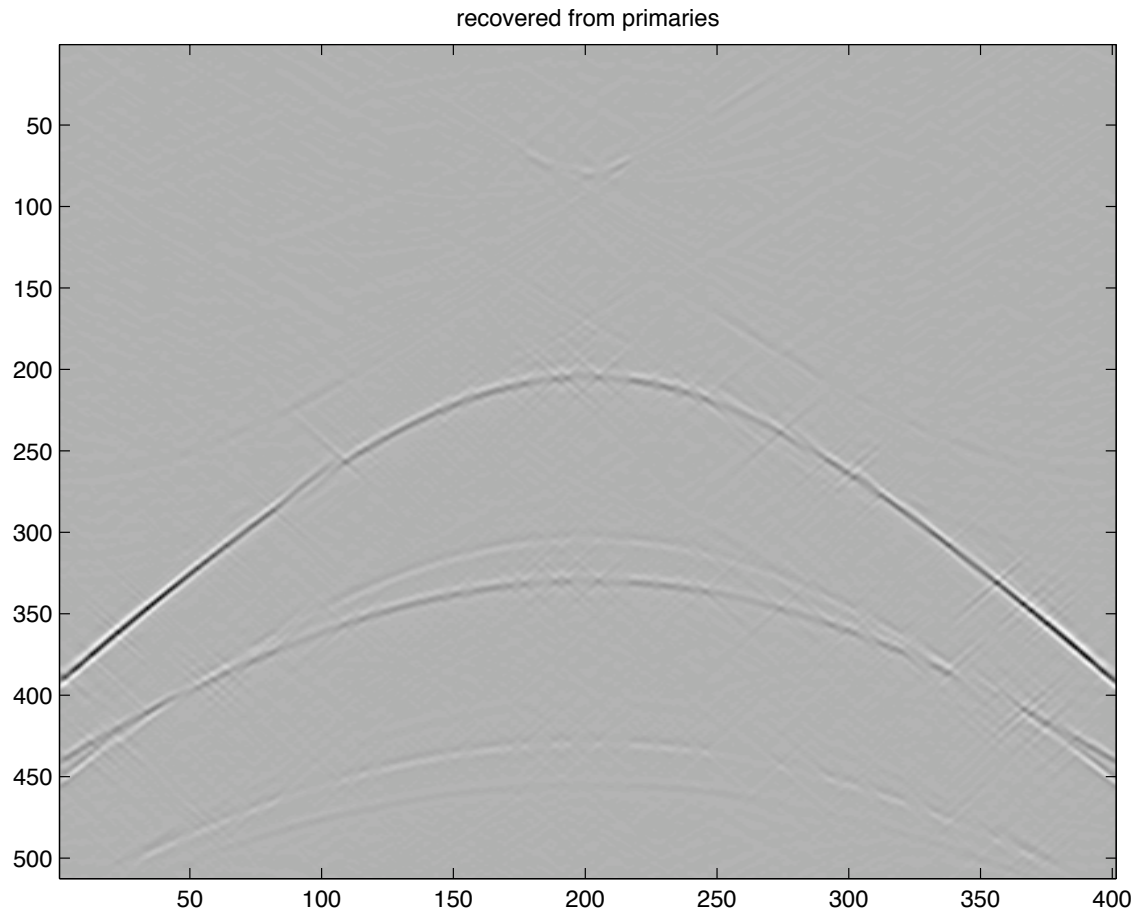
True multiples



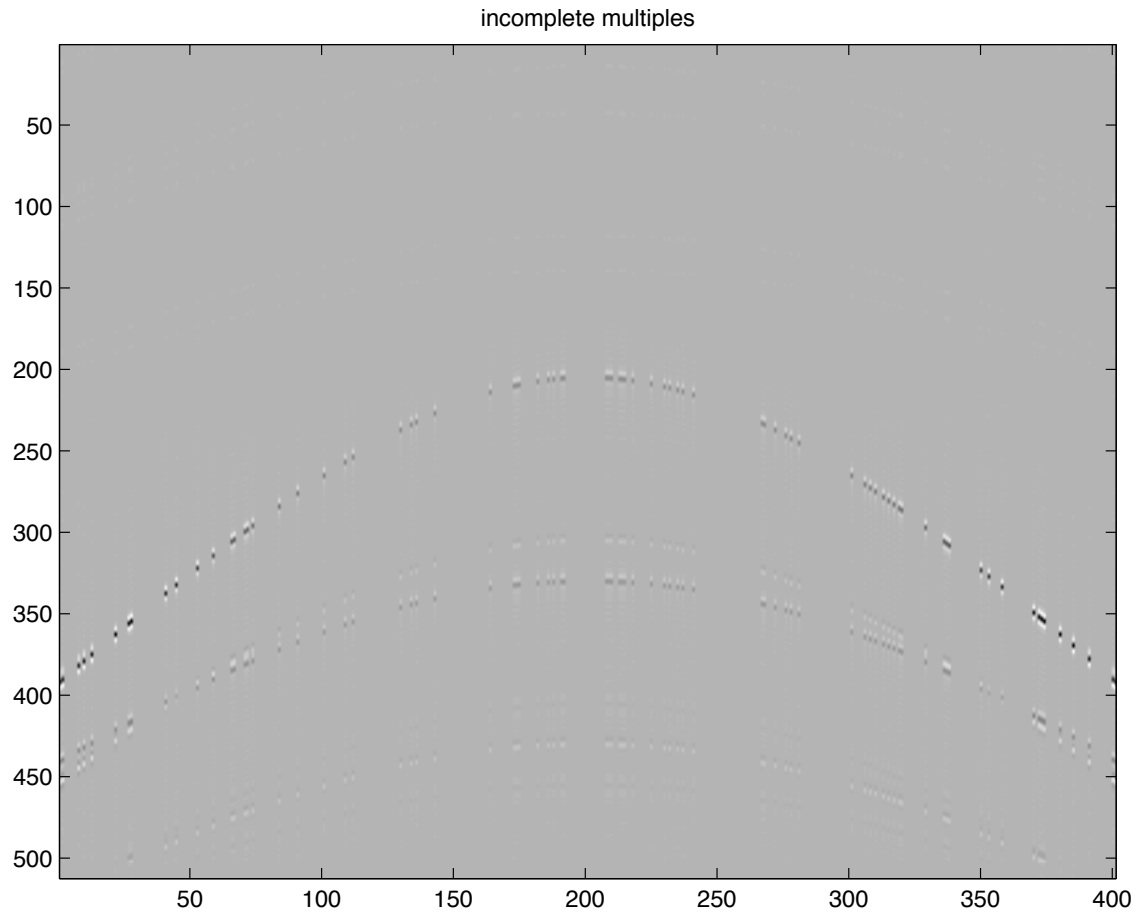
Incomplete multiples



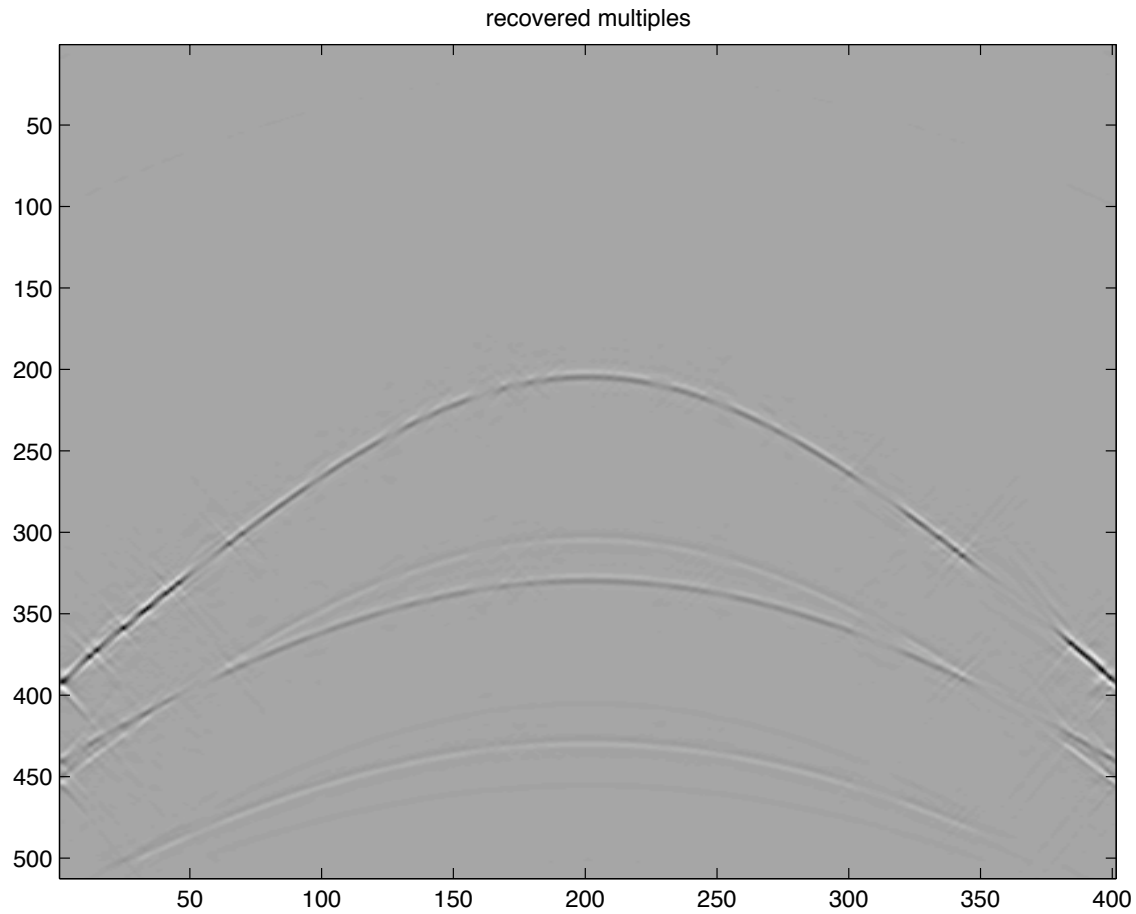
Recovered multiples



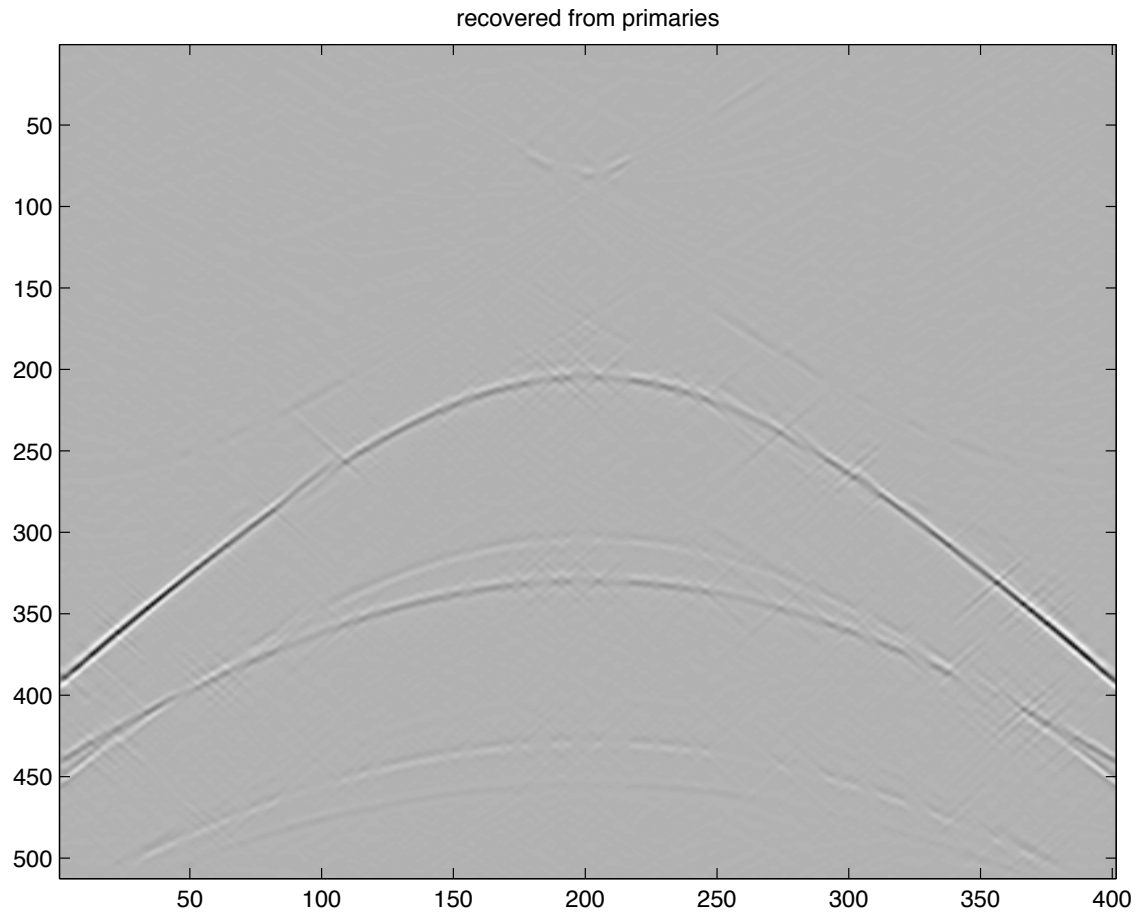
Incomplete multiples



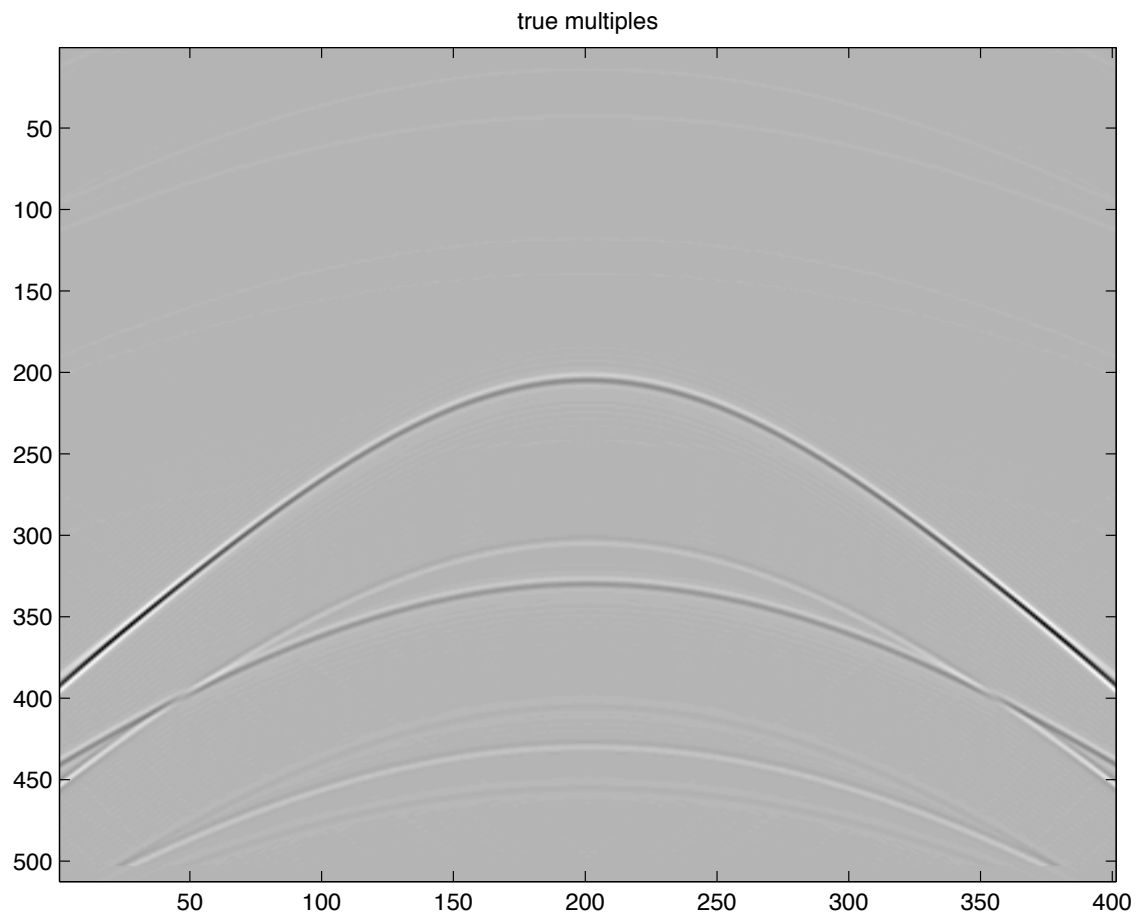
Interpolated multiples



Recovered multiples

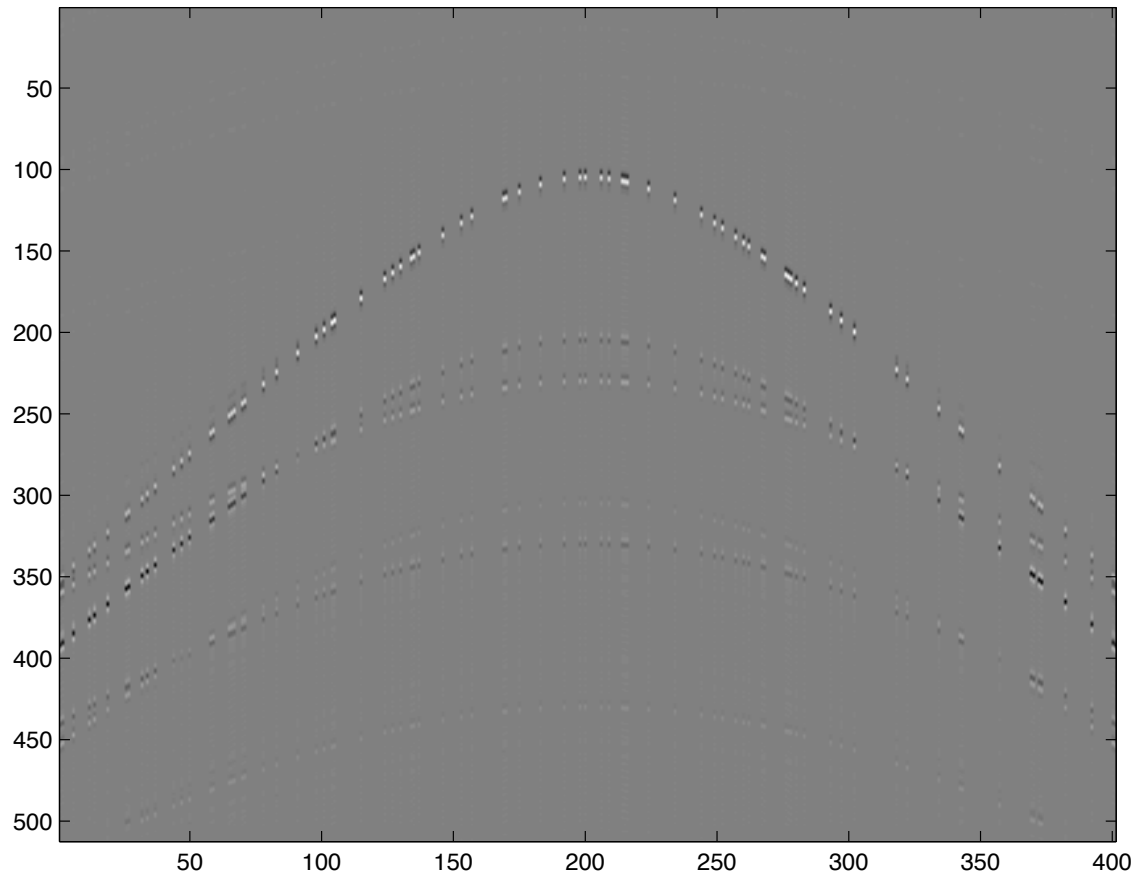


True multiples

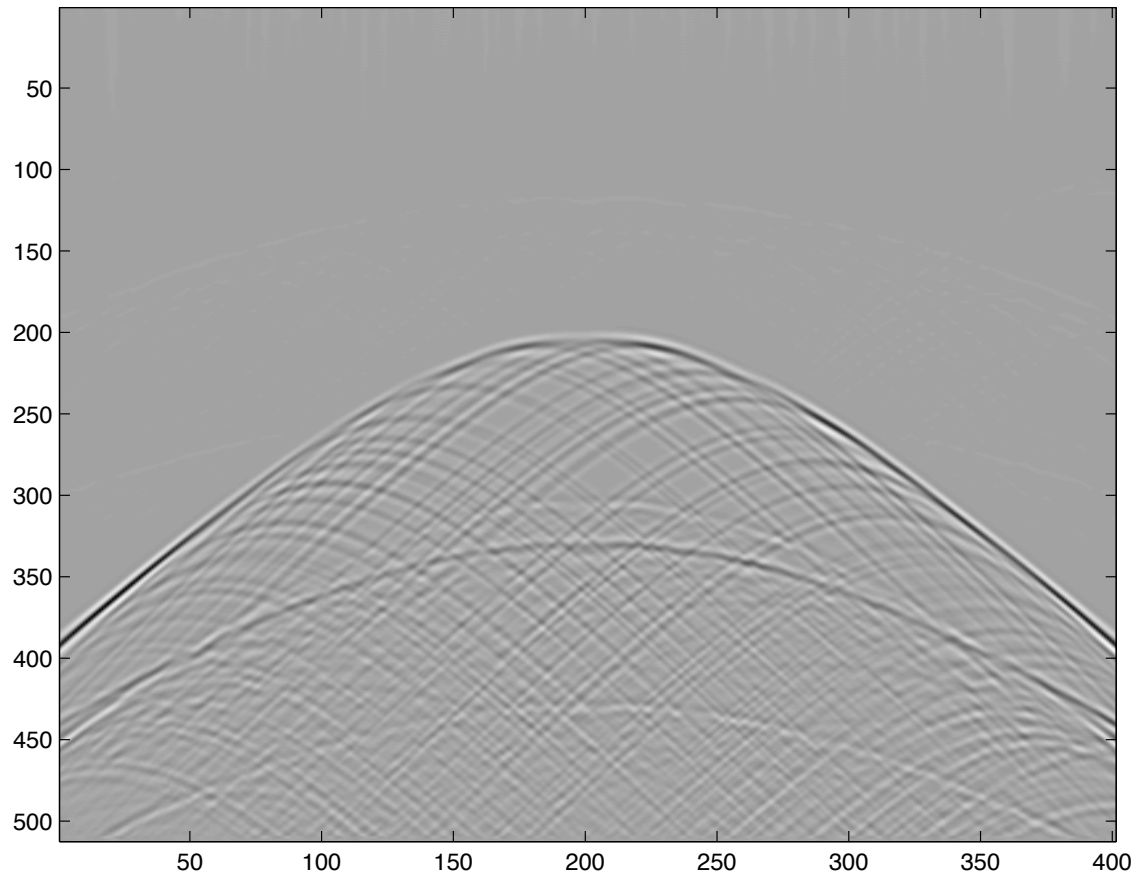


Data

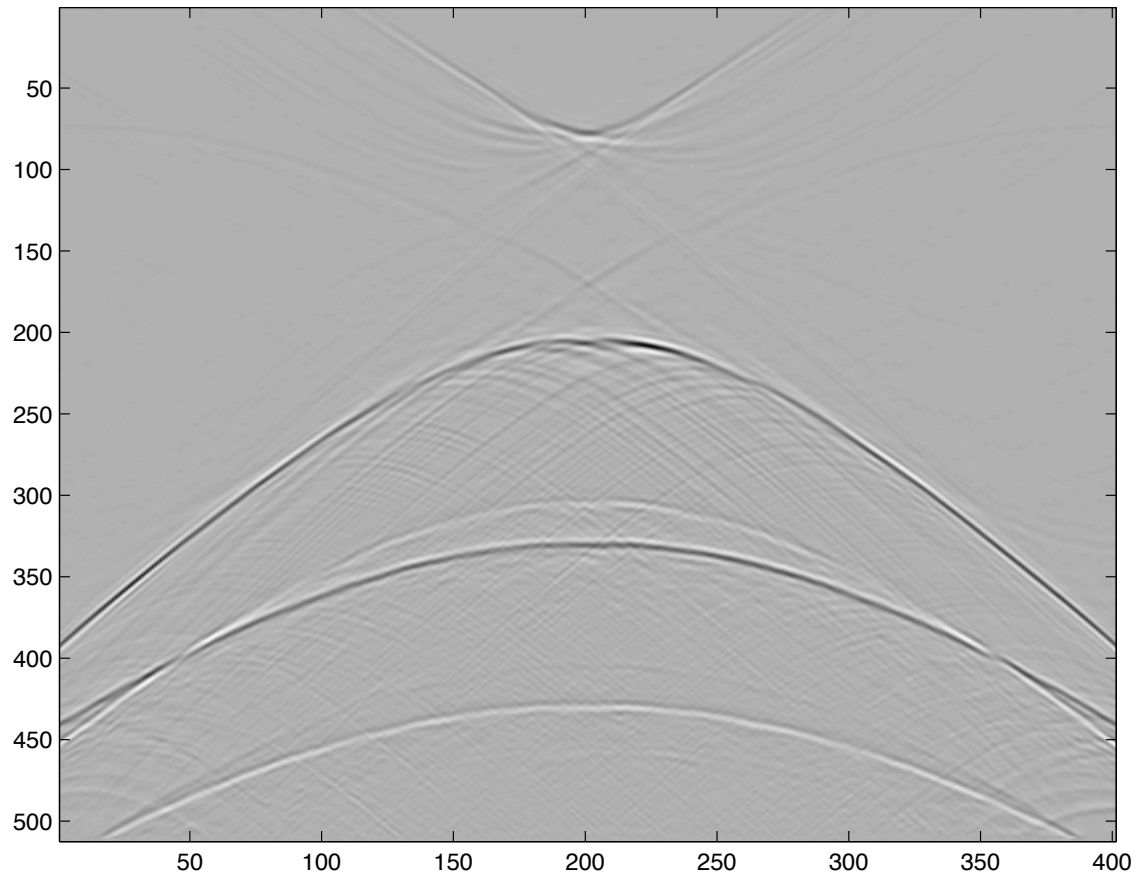
missing data



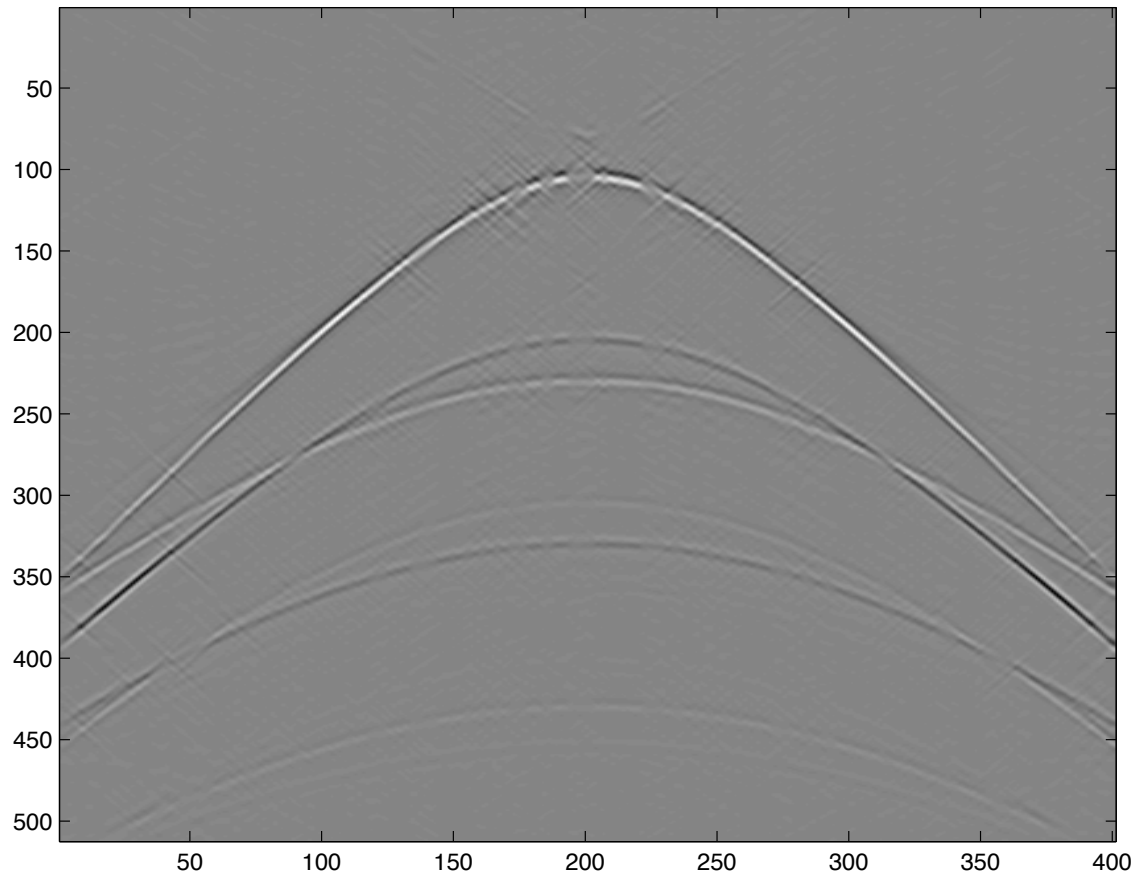
mapped multiples



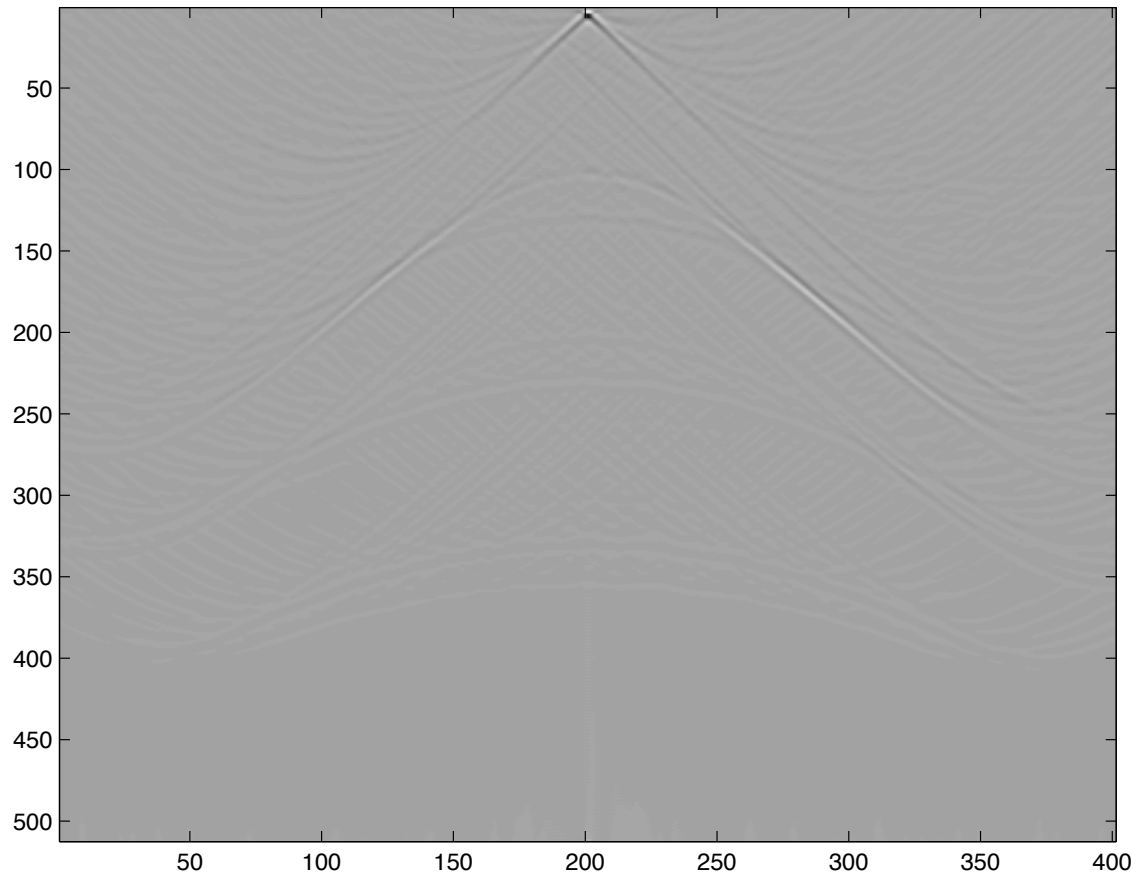
inverted multiples



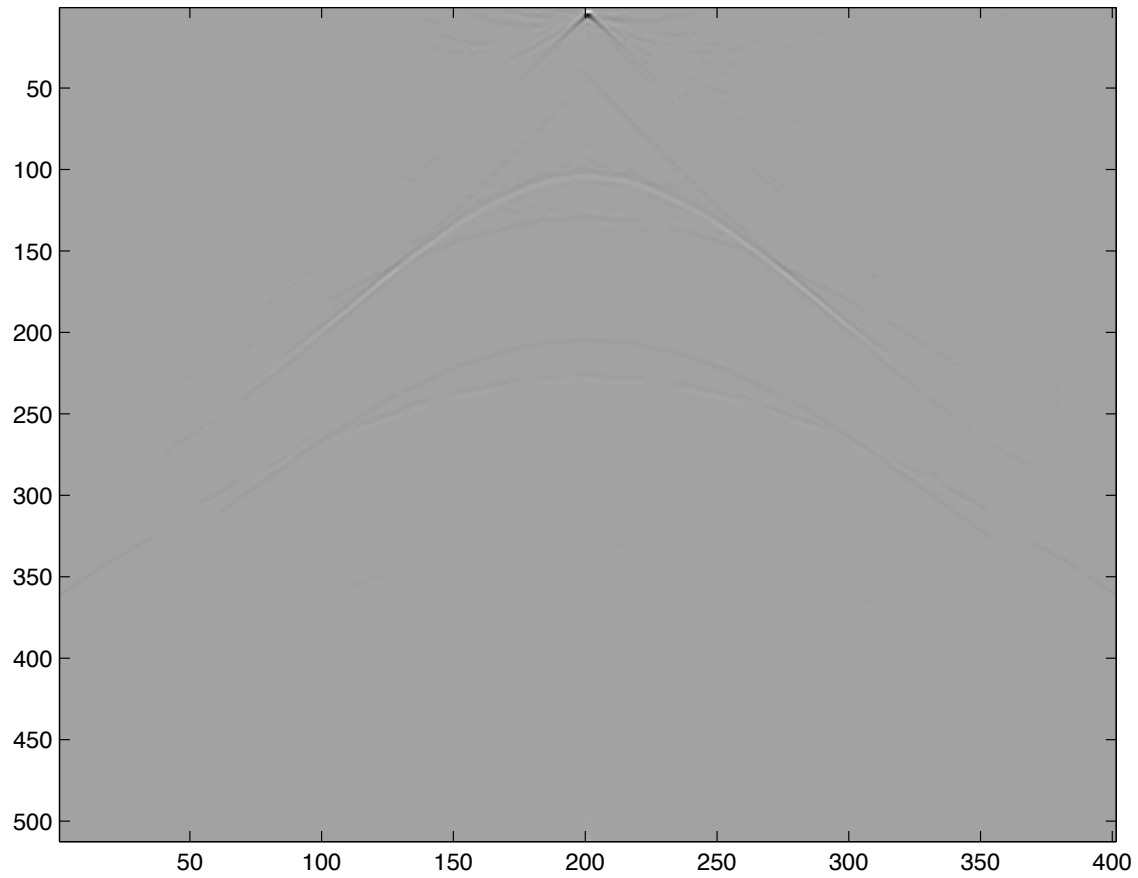
recovered from multiples



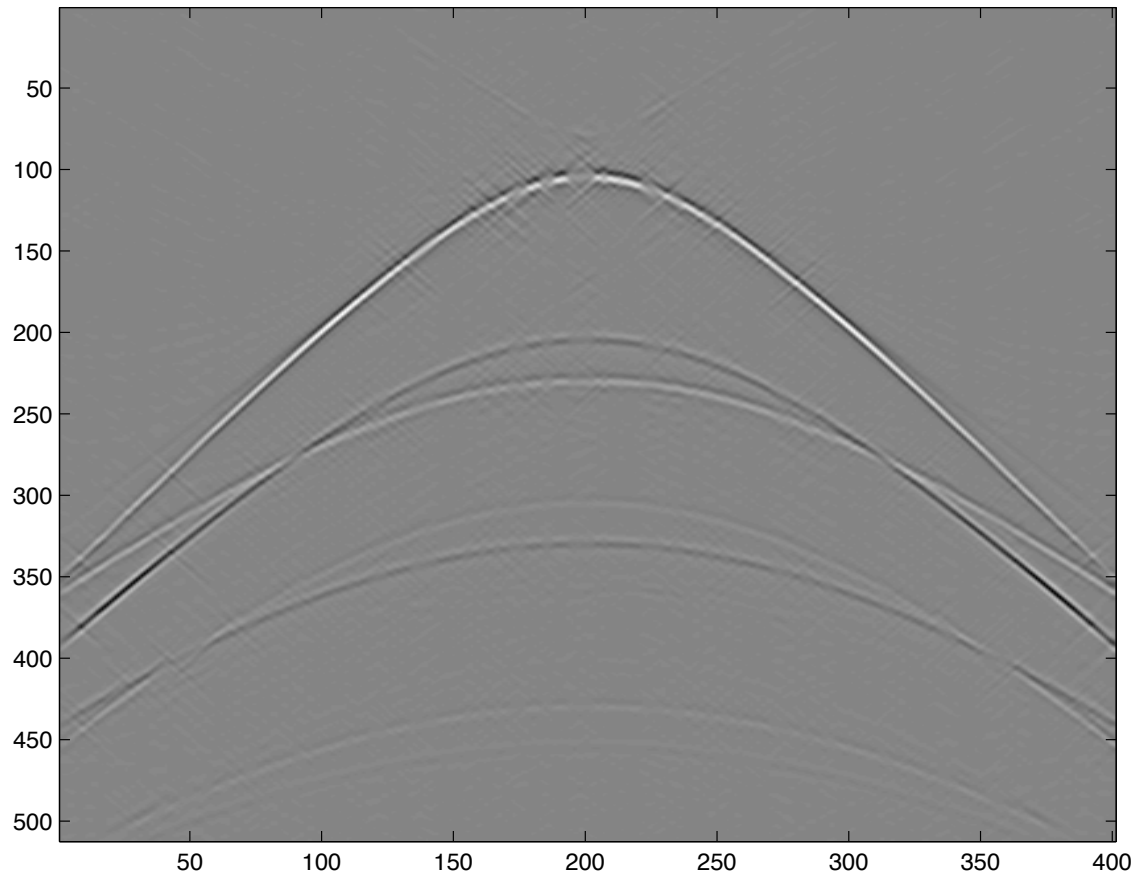
mapped primaries



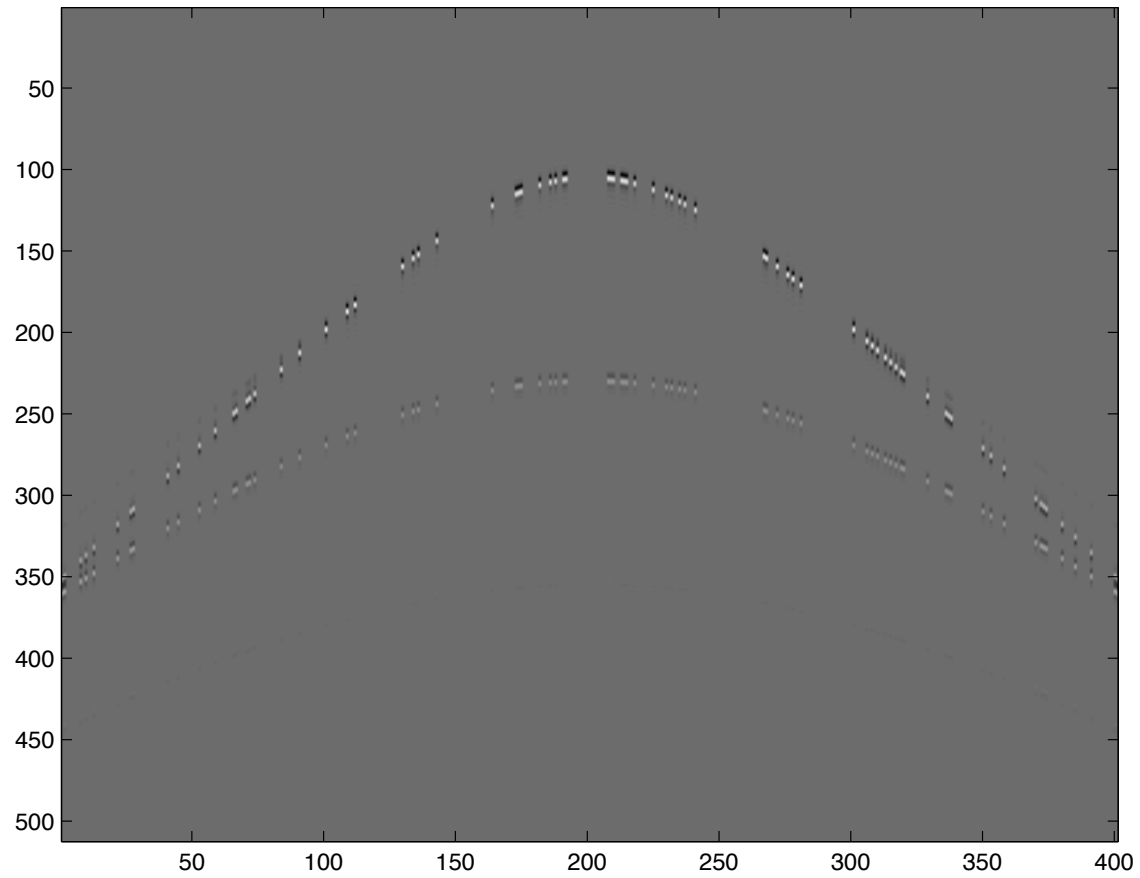
inverted primaries



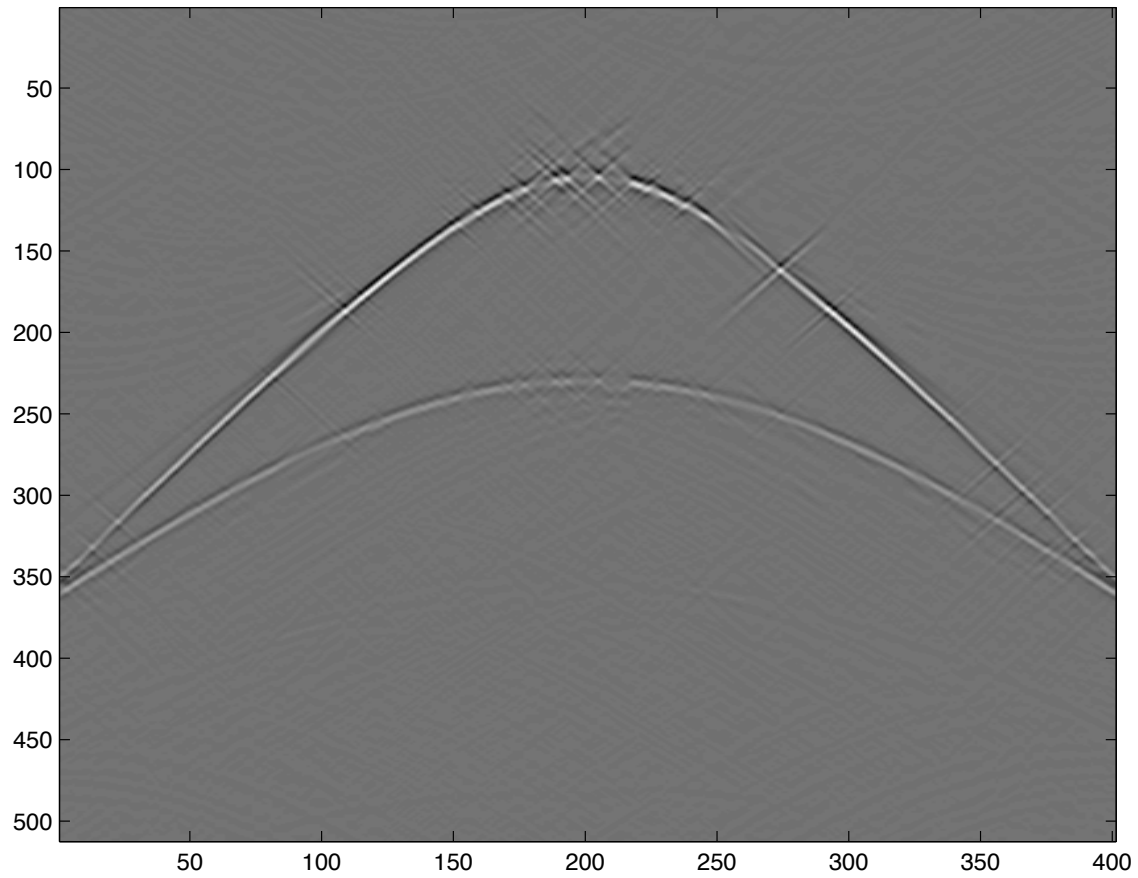
recovered from primaries

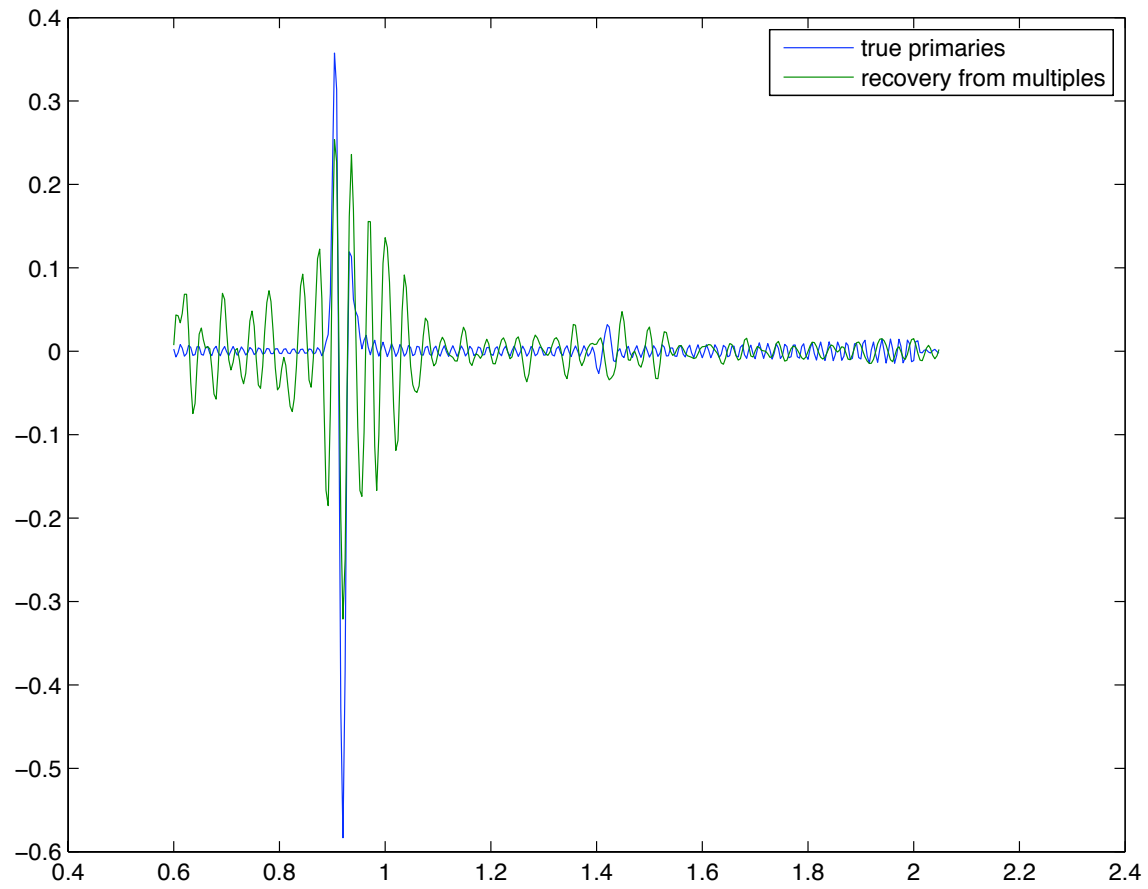


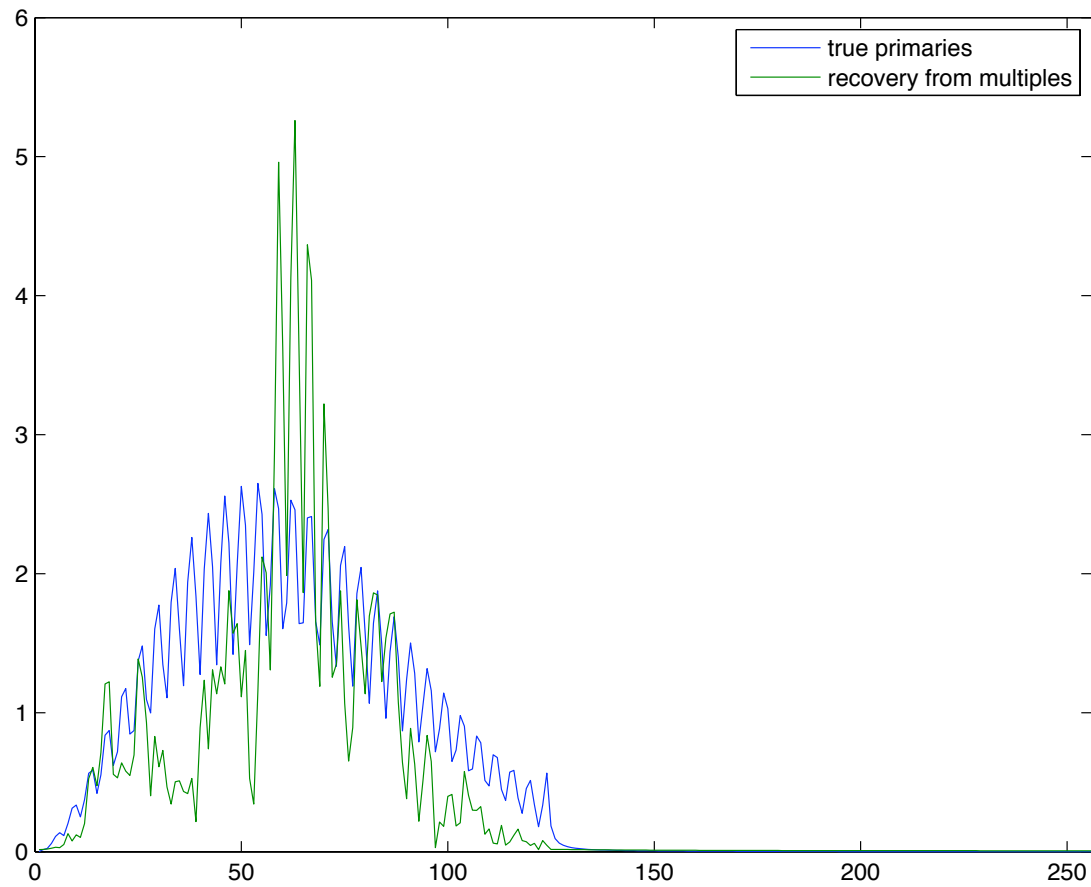
incomplete primaries



recovered from multiples







Tentative observations

Exploiting sparsity omits “inversion” of acquisition.

Inverting the cross-convolution enhances sparsity.

Recovery is uplifted by the physics of focussing.

Opens the perspective of formulating a program

- stably separates data into its different constituents
- recovers missing data with transform-based techniques compounded with the physics of cross-correlations and cross-convolutions

Opens the pathway towards nonlinear inversion