

# Implicit interpolation of trace gaps in REPSI using auto-convolution terms

Tim T.Y. Lin

## Talk outline

Brief review of REPSI

Data reconstruction in EPSI

*Eliminate explicit expression for missing data*

Field data example

## From SRME to Robust EPSI

Based on **Estimation of Primaries by Sparse Inversion** (van Groenestijn and Verschuur, 2009)

true primary wavefield

SRME-produced primary

$$\mathbf{P}_o = \mathbf{P} - A(f)\mathbf{P}_o\mathbf{P}$$

$\mathbf{P}$  total up-going wavefield  
 $\mathbf{P}_o$  primary wavefield  
 $A(f)$  “matching” operator

## From SRME to Robust EPSI

Based on **Estimation of Primaries by Sparse Inversion** (van Groenestijn and Verschuur, 2009)

true primary wavefield

SRME-produced primary

$$\mathbf{P}_o \approx \mathbf{P} - A(f) \mathbf{P} \mathbf{P}$$

SRMP

$\mathbf{P}$  total up-going wavefield

$\mathbf{P}_o$  primary wavefield

$A(f)$  “matching” operator

## From SRME to Robust EPSI

Based on **Estimation of Primaries by Sparse Inversion** (van Groenestijn and Verschuur, 2009)

**adaptive subtraction**

$$\min_A \sum_f \|\mathbf{P} - A(f) \mathbf{P}\|$$

**SRMP**

$\mathbf{P}$  total up-going wavefield  
 $\mathbf{P}_o$  primary wavefield  
 $A(f)$  “matching” operator

## From SRME to Robust EPSI

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# From SRME to Robust EPSI

Based on **Estimation of Primaries by Sparse Inversion** (van Groenestijn and Verschuur, 2009)

recorded data      predicted data from SRME

$$\mathbf{P} = \mathbf{P}_o + A(f)\mathbf{P}_o\mathbf{P}$$

$\mathbf{P}$       total up-going wavefield  
 $\mathbf{P}_o$       primary wavefield  
 $A(f)$       “matching” operator

## From SRME to Robust EPSI

Based on **Estimation of Primaries by Sparse Inversion** (van Groenestijn and Verschuur, 2009)

recorded data      predicted data from SRME

$$\mathbf{P} = \mathbf{P}_o + A(f)\mathbf{P}_o\mathbf{P}$$

$$\begin{aligned}\mathbf{P}_o &= \mathbf{Q}\mathbf{G} \\ A(f) &= -\mathbf{Q}^{-1}\end{aligned}$$

**P**      total up-going wavefield  
**Q**      down-going source signature  
**G**      primary impulse response



# From SRME to Robust EPSI

Based on **Estimation of Primaries by Sparse Inversion** (van Groenestijn and Verschuur, 2009)

recorded data      predicted data from SRME

$$\mathbf{P} = \mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P}$$

- P**      total up-going wavefield
- Q**      down-going source signature
- G**      primary impulse response

## From SRME to Robust EPSI

Based on **Estimation of Primaries by Sparse Inversion** (van Groenestijn and Verschuur, 2009)

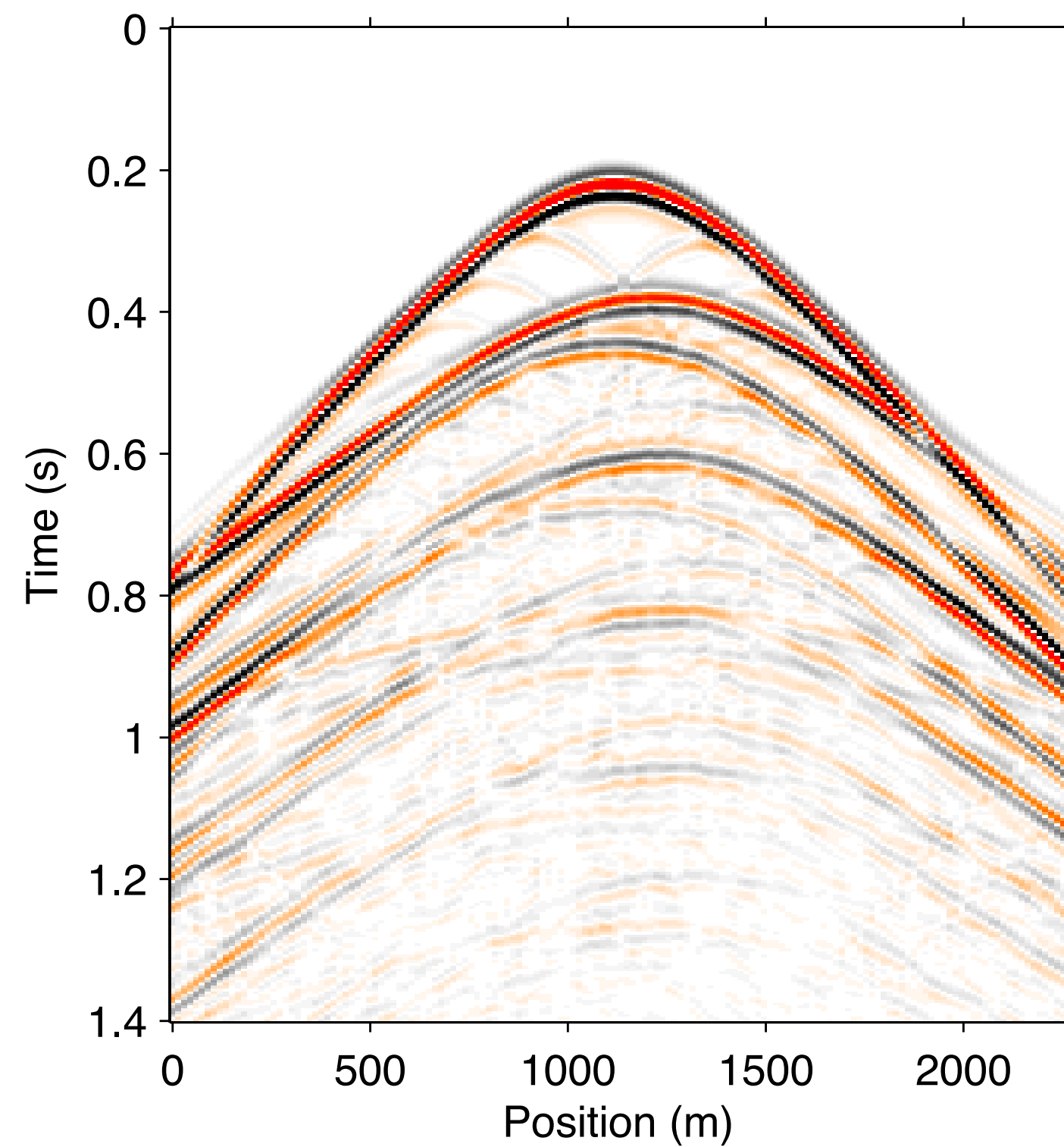
recorded data      predicted data from SRME

$$\mathbf{P} = \mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P}$$

**Inversion objective:**

$$f(\mathbf{G}, \mathbf{Q}) = \frac{1}{2} \|\mathbf{P} - (\mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P})\|_2^2$$

# From SRME to Robust EPSI



**Primaries by Sparse Inversion** (van Groenestijn and Verschuur, 2009)

observed data predicted data from SRME

$$\mathbf{P} = \mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P}$$

$$f(\mathbf{G}, \mathbf{Q}) = \frac{1}{2} \|\mathbf{P} - (\mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P})\|_2^2$$

# From SRME to Robust EPSI

Based on **Estimation of Primaries by Sparse Inversion** (van

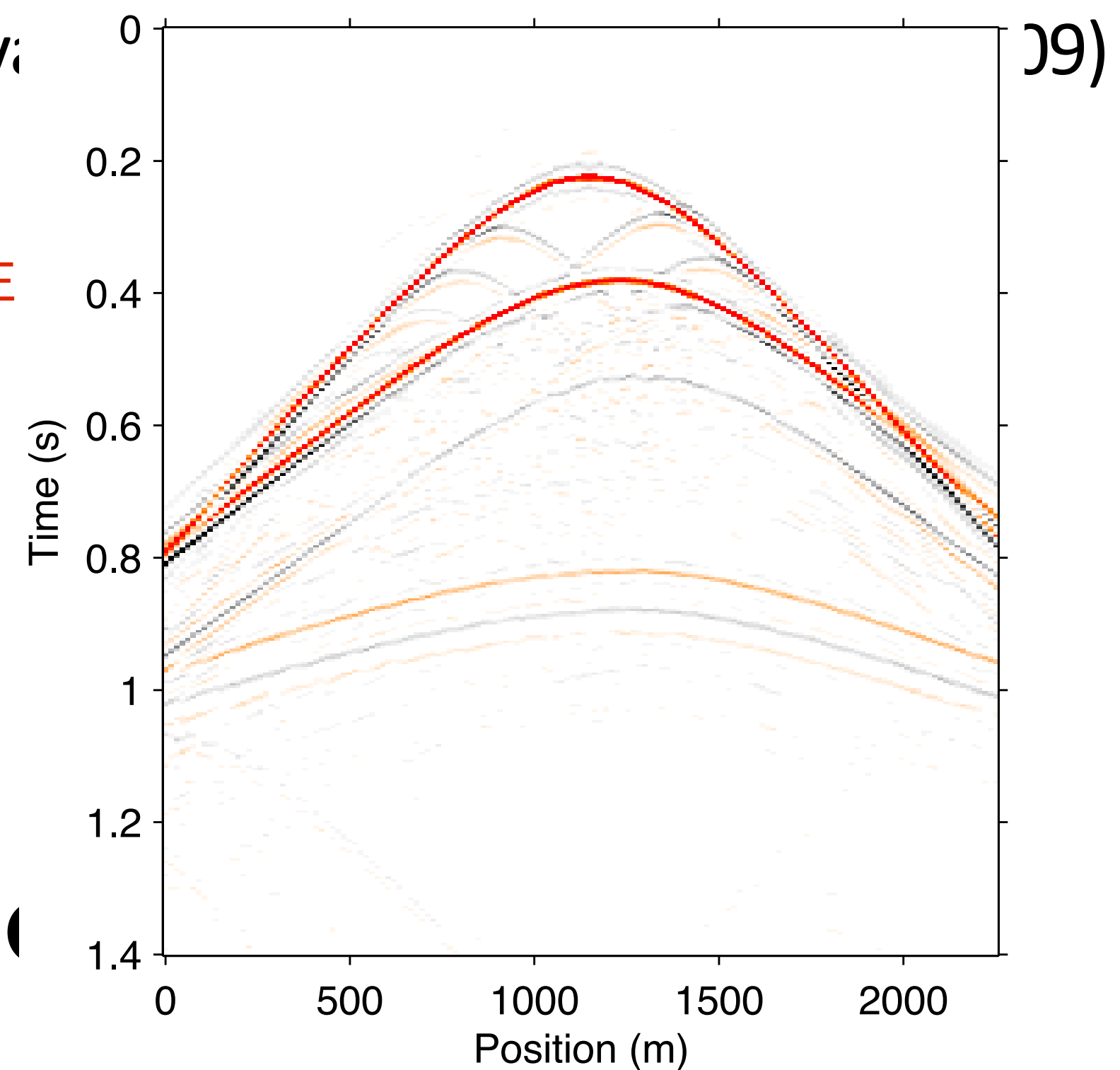
recorded data

predicted data from SRME

$$\mathbf{P} = \mathbf{Q}\mathbf{G} + \mathbf{G}\mathbf{P}$$

**Inversion objective:**

$$f(\mathbf{G}, \mathbf{Q}) = \frac{1}{2} \|\mathbf{P} - (\mathbf{Q}\mathbf{G} + \mathbf{G}\mathbf{P})\|$$



# From SRME to Robust EPSI

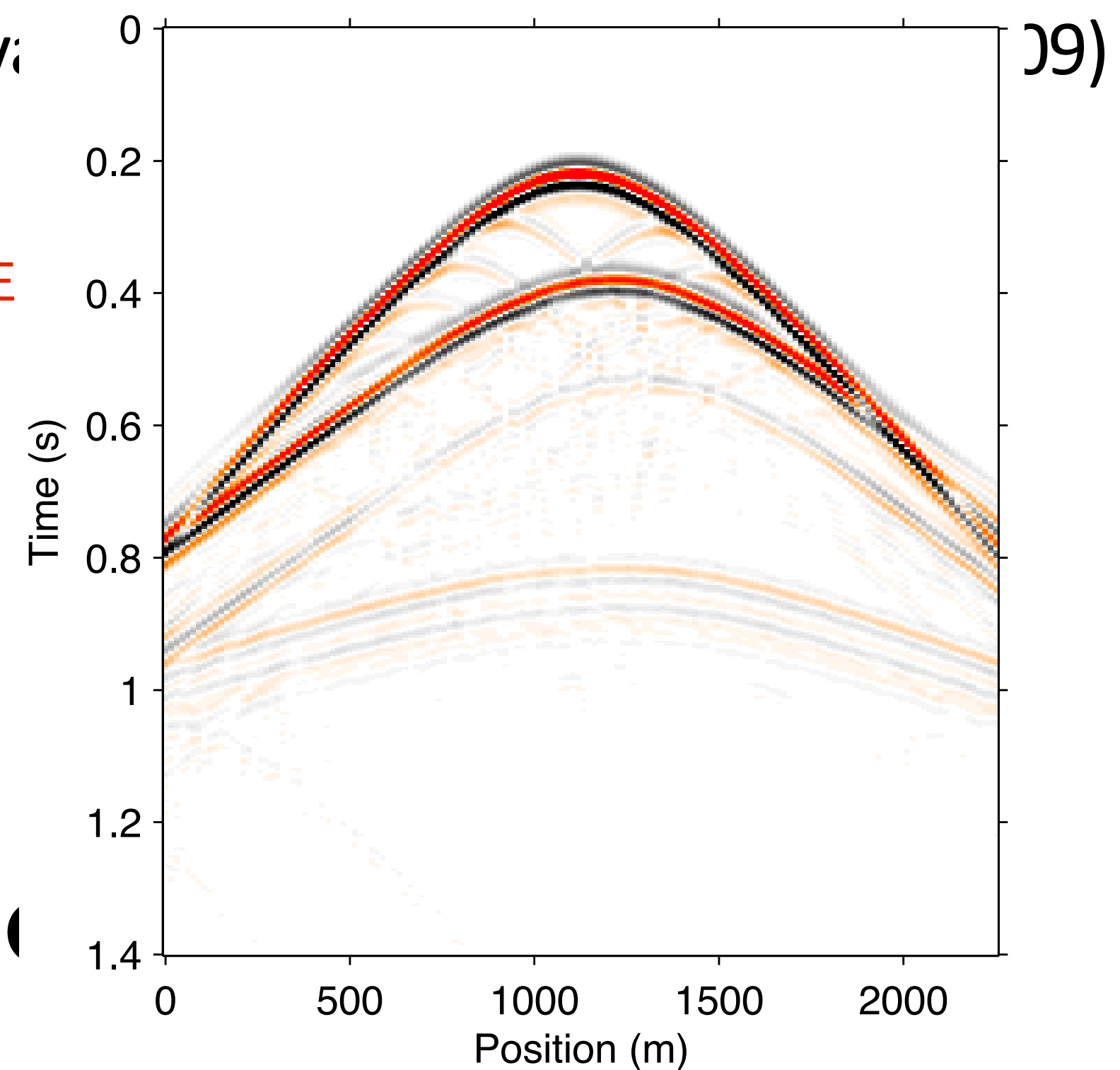
Based on **Estimation of Primaries by Sparse Inversion** (van

$$\mathbf{P} = \underbrace{\mathbf{Q}\mathbf{G}}_{\text{predicted data from SRME}} - \mathbf{G}\mathbf{P}$$

recorded data

**Inversion objective:**

$$f(\mathbf{G}, \mathbf{Q}) = \frac{1}{2} \|\mathbf{P} - (\mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P})\|$$



# From SRME to Robust EPSI

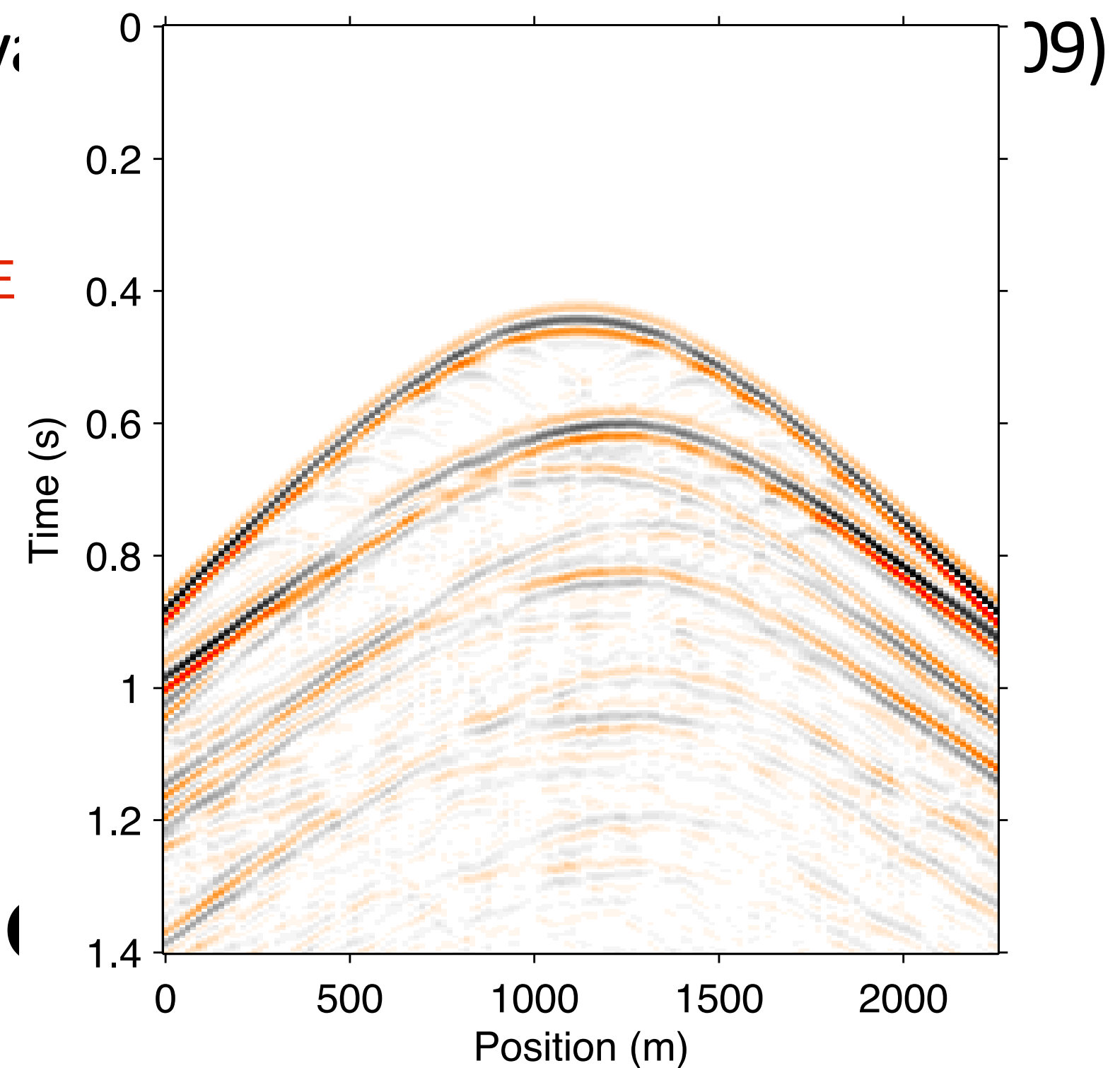
Based on **Estimation of Primaries by Sparse Inversion** (van

recorded data      predicted data from SRME

$$\mathbf{P} = \mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P}$$

**Inversion objective:**

$$f(\mathbf{G}, \mathbf{Q}) = \frac{1}{2} \|\mathbf{P} - (\mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P})\|$$



# From SRME to Robust EPSI

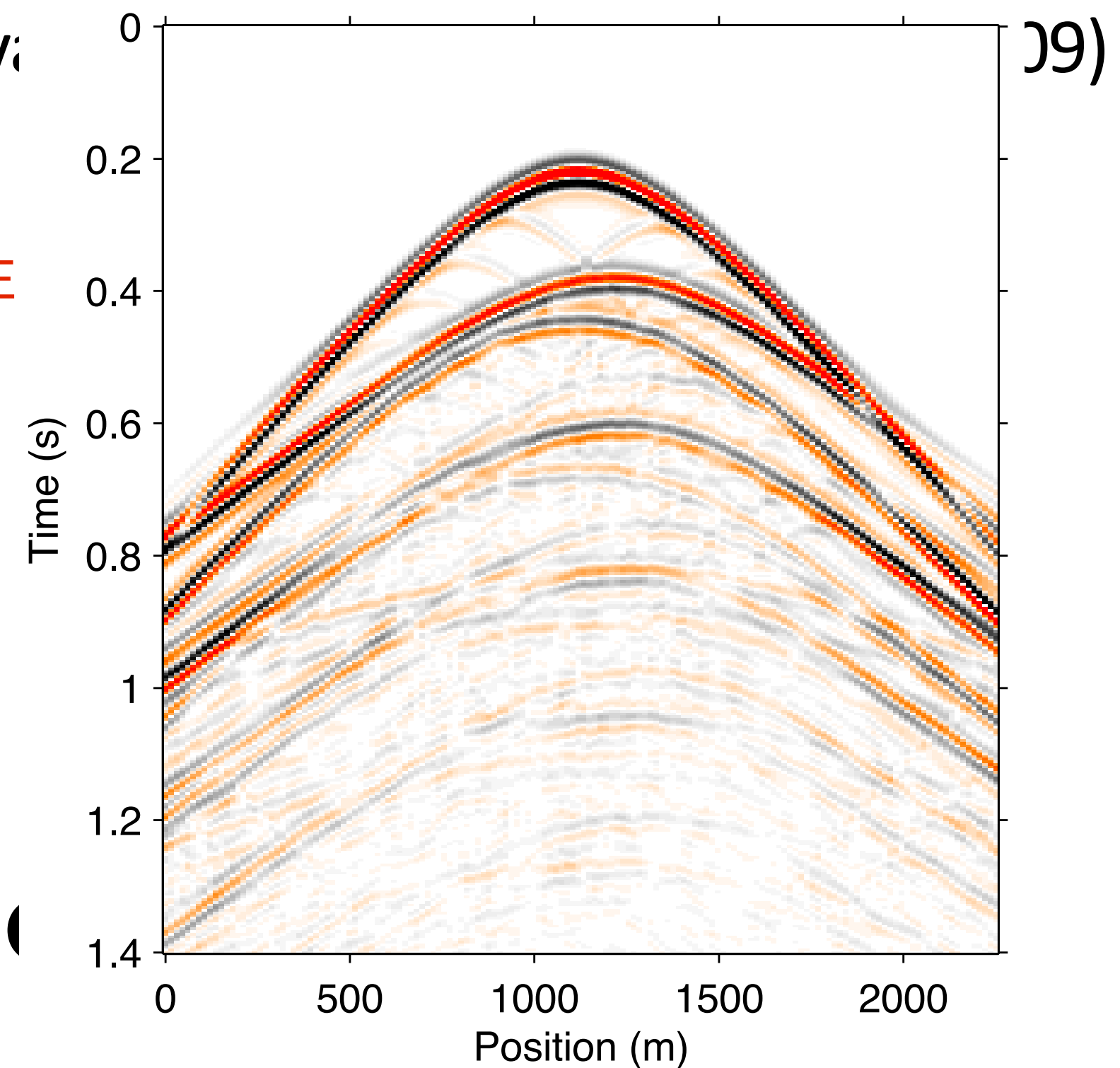
Based on **Estimation of Primaries by Sparse Inversion** (van

recorded data      predicted data from SRME

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**Inversion objective:**

$$f(\mathbf{G}, \mathbf{Q}) = \frac{1}{2} \|\mathbf{P} - (\mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P})\|$$



09)

## From SRME to Robust EPSI

Based on **Estimation of Primaries by Sparse Inversion** (van Groenestijn and Verschuur, 2009)

recorded data      predicted data from SRME

$$\mathbf{P} = \mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P}$$

**Inversion objective:**

$$f(\mathbf{G}, \mathbf{Q}) = \frac{1}{2} \|\mathbf{P} - (\mathbf{Q}\mathbf{G} - \mathbf{G}\mathbf{P})\|_2^2$$



## From SRME to Robust EPSI

Two ways to obtain the final primary wavefield

“Direct” Primary      “Conservative” Primary

$$\mathbf{QG} = \mathbf{P} + \mathbf{GP}$$

**Inversion objective:**

$$f(\mathbf{G}, \mathbf{Q}) = \frac{1}{2} \|\mathbf{P} - (\mathbf{QG} - \mathbf{GP})\|_2^2$$

# From SRME to Robust EPSI

**In time domain** (lower-case: whole dataset in time domain)

recorded data      predicted data from SRME

$$\mathbf{p} = \mathcal{M}(\mathbf{g}, \mathbf{q})$$

$$\mathcal{M}(\mathbf{g}, \mathbf{q}) := \mathcal{F}_t^\dagger \text{BlockDiag}_{\omega_1 \dots \omega_{n_f}} [(q(\omega)\mathbf{I} - \mathbf{P})^\dagger \otimes \mathbf{I}] \mathcal{F}_t \mathbf{g}$$

**Inversion objective:**

$$f(\mathbf{g}, \mathbf{q}) = \frac{1}{2} \|\mathbf{p} - \mathcal{M}(\mathbf{g}, \mathbf{q})\|_2^2$$

# Solving the EPSI problem

## Linearizations

$$\mathbf{p} = \mathcal{M}(\mathbf{g}, \mathbf{q})$$

$$\mathbf{M}_{\tilde{\mathbf{q}}} = \left( \frac{\partial \mathcal{M}}{\partial \mathbf{g}} \right)_{\tilde{\mathbf{q}}}$$

$$\mathbf{M}_{\tilde{\mathbf{g}}} = \left( \frac{\partial \mathcal{M}}{\partial \mathbf{q}} \right)_{\tilde{\mathbf{g}}}$$

In fact it is bilinear:  $\mathbf{Q}\mathbf{G} = \mathbf{P} + \mathbf{G}\mathbf{P}$

$$\mathbf{M}_{\tilde{\mathbf{q}}}\mathbf{g} = \mathcal{M}(\mathbf{g}, \tilde{\mathbf{q}}) \quad \mathbf{M}_{\tilde{\mathbf{g}}}\mathbf{q} = \mathcal{M}(\mathbf{q}, \tilde{\mathbf{g}})$$

# Solving the EPSI problem

## Linearizations

$$\mathbf{p} = \mathcal{M}(\mathbf{g}, \mathbf{q})$$

$$\mathbf{M}_{\tilde{q}} = \left( \frac{\partial \mathcal{M}}{\partial \mathbf{g}} \right)_{\tilde{q}}$$

$$\mathbf{M}_{\tilde{g}} = \left( \frac{\partial \mathcal{M}}{\partial \mathbf{q}} \right)_{\tilde{g}}$$

## Associated objectives:

$$f_{\tilde{q}}(\mathbf{g}) = \frac{1}{2} \|\mathbf{p} - \mathbf{M}_{\tilde{q}} \mathbf{g}\|_2^2$$

$$f_{\tilde{g}}(\mathbf{q}) = \frac{1}{2} \|\mathbf{p} - \mathbf{M}_{\tilde{g}} \mathbf{q}\|_2^2$$

# Solving the EPSI problem

**Do:**

$$\mathbf{g}_{k+1} = \mathbf{g}_k + \alpha \mathcal{S}(\nabla f_{q_k}(\mathbf{g}_k))$$

$$\mathbf{q}_{k+1} = \mathbf{q}_k + \beta \nabla f_{g_{k+1}}(\mathbf{q}_k)$$

**Gradient sparsity**

$\mathcal{S}$  : pick largest  $\rho$  elements per trace

# 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  $\tau_k$  from the Pareto curve

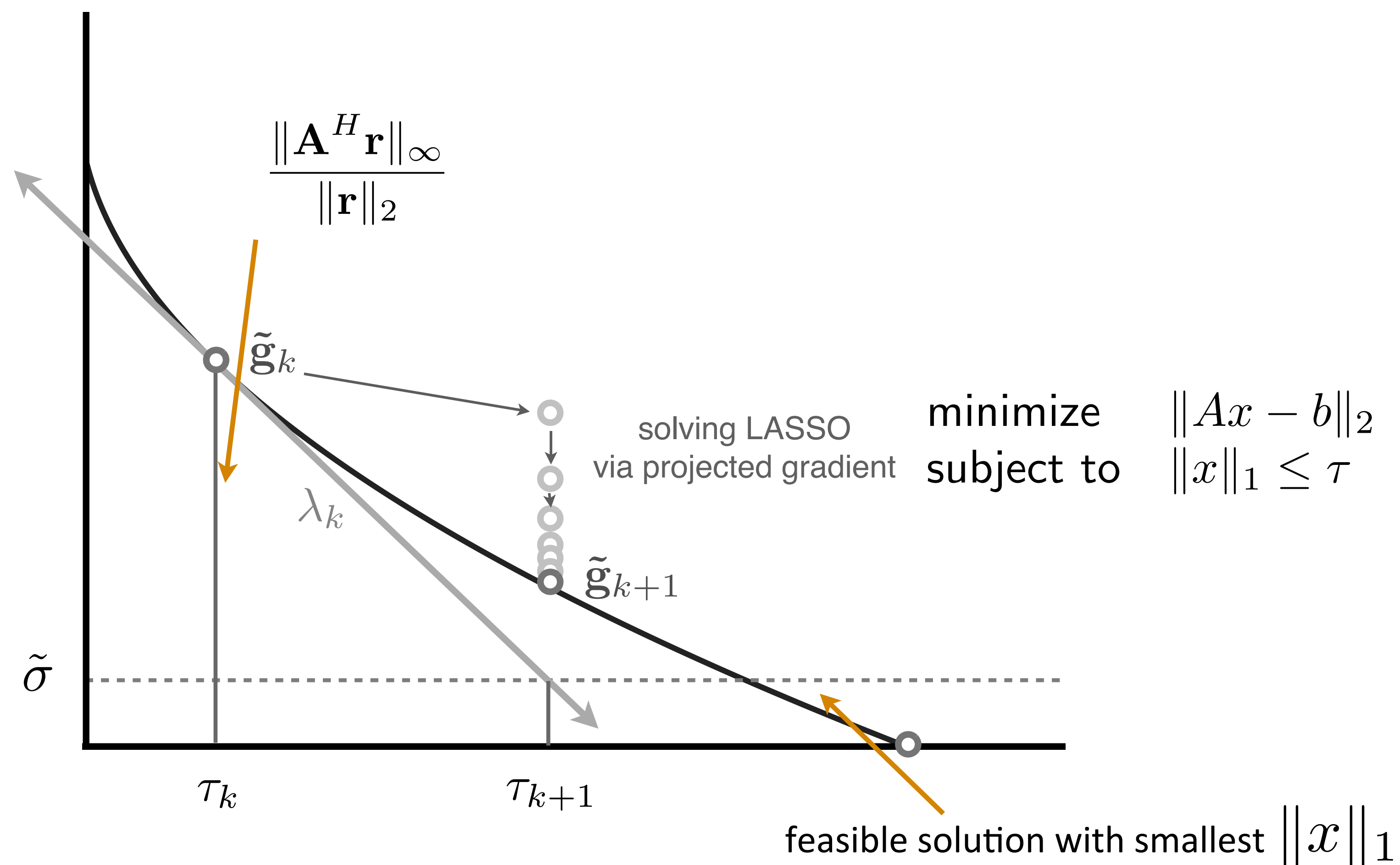
$$\mathbf{g}_{k+1} = \arg \min_{\mathbf{g}} \|\mathbf{p} - \mathbf{M}_{q_k} \mathbf{g}\|_2 \text{ s.t. } \|\mathbf{g}\|_1 \leq \tau_k$$

$$\mathbf{q}_{k+1} = \arg \min_{\mathbf{q}} \|\mathbf{p} - \mathbf{M}_{g_{k+1}} \mathbf{q}\|_2$$

# Choosing Tau from the Pareto curve

$$\begin{aligned} &\text{minimize} && \|x\|_1 \\ &\text{subject to} && \|Ax - b\|_2 \leq \sigma \end{aligned}$$

Look at the solution space and the line of optimal solutions (Pareto curve)



Inverting for unknown data



# Robust EPSI

Inverting for unknown data

$$\Delta \mathbf{P}(\mathbf{G}_{k+1}, \mathbf{R}_{k+1}) := -(\mathbf{I} + \mathbf{G}_{k+1})^H (\mathbf{R}_{k+1})$$

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

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

$$\mathbf{q}_{k+1} = \arg \min_{\mathbf{q}} \|\mathbf{p}_k - \mathbf{M}_{g_{k+1}} \mathbf{q}\|_2$$

$$\mathbf{p}_{k+1} = \mathbf{p}_k + \alpha \Delta \mathbf{p}(\mathbf{g}_{k+1}, \mathbf{q}_{k+1}, \mathbf{p}_k)$$

# Robust EPSI

## Inverting for unknown data

Data changes every iteration!

$$\Delta \mathbf{P}(\mathbf{G}_{k+1}, \mathbf{R}_{k+1}) := -(\mathbf{I} + \mathbf{G}_{k+1})^H (\mathbf{R}_{k+1})$$

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

determine new  $\tau_k$  from the Pareto curve

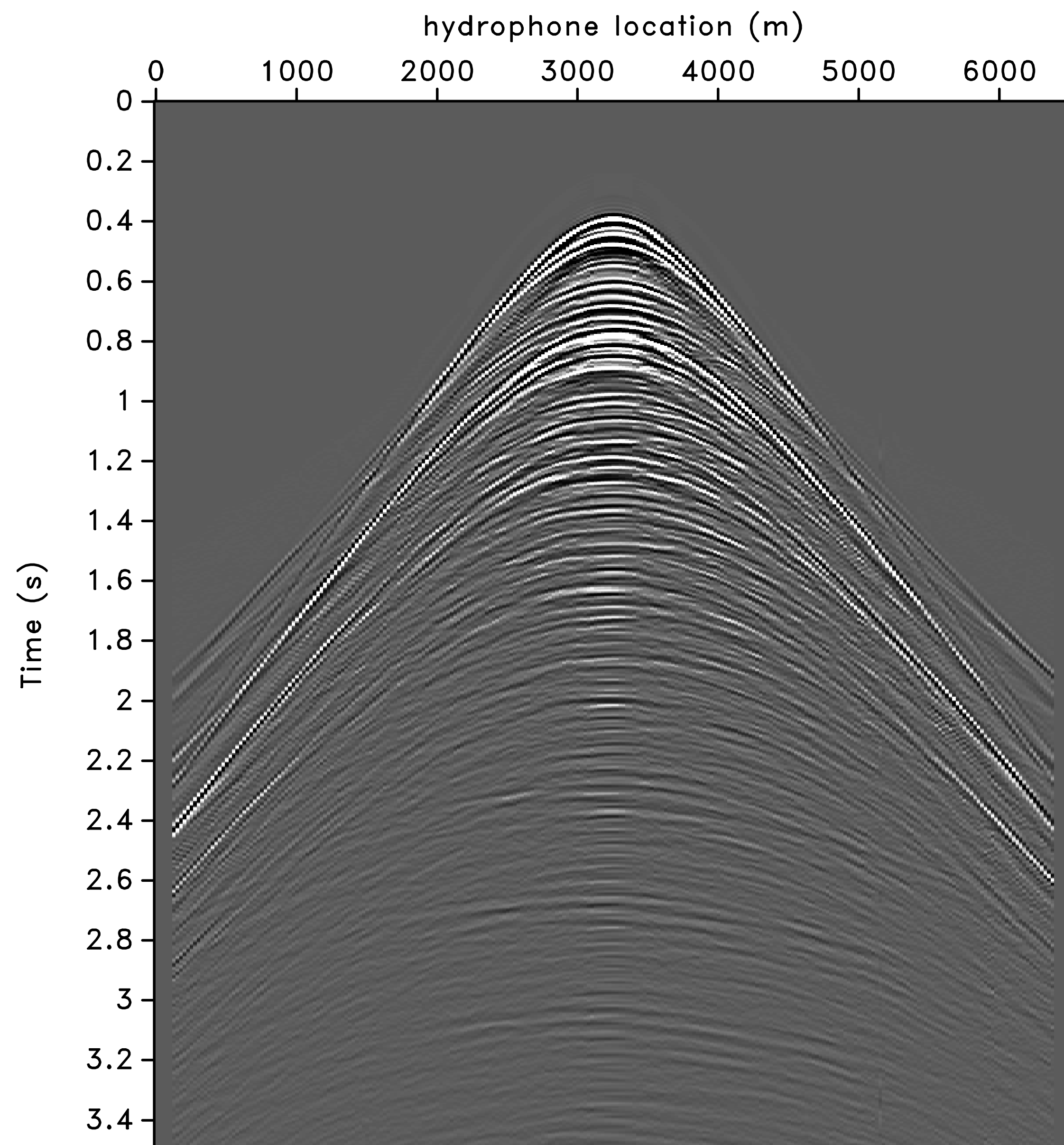
$$\mathbf{g}_{k+1} = \arg \min_{\mathbf{g}} \|\mathbf{p}_k - \mathbf{M}_{\mathbf{q}_k} \mathbf{g}\|_2 \text{ s.t. } \|\mathbf{g}\|_1 \leq \tau_k$$

$$\mathbf{q}_{k+1} = \arg \min_{\mathbf{q}} \|\mathbf{p}_k - \mathbf{M}_{\mathbf{g}_{k+1}} \mathbf{q}\|_2$$

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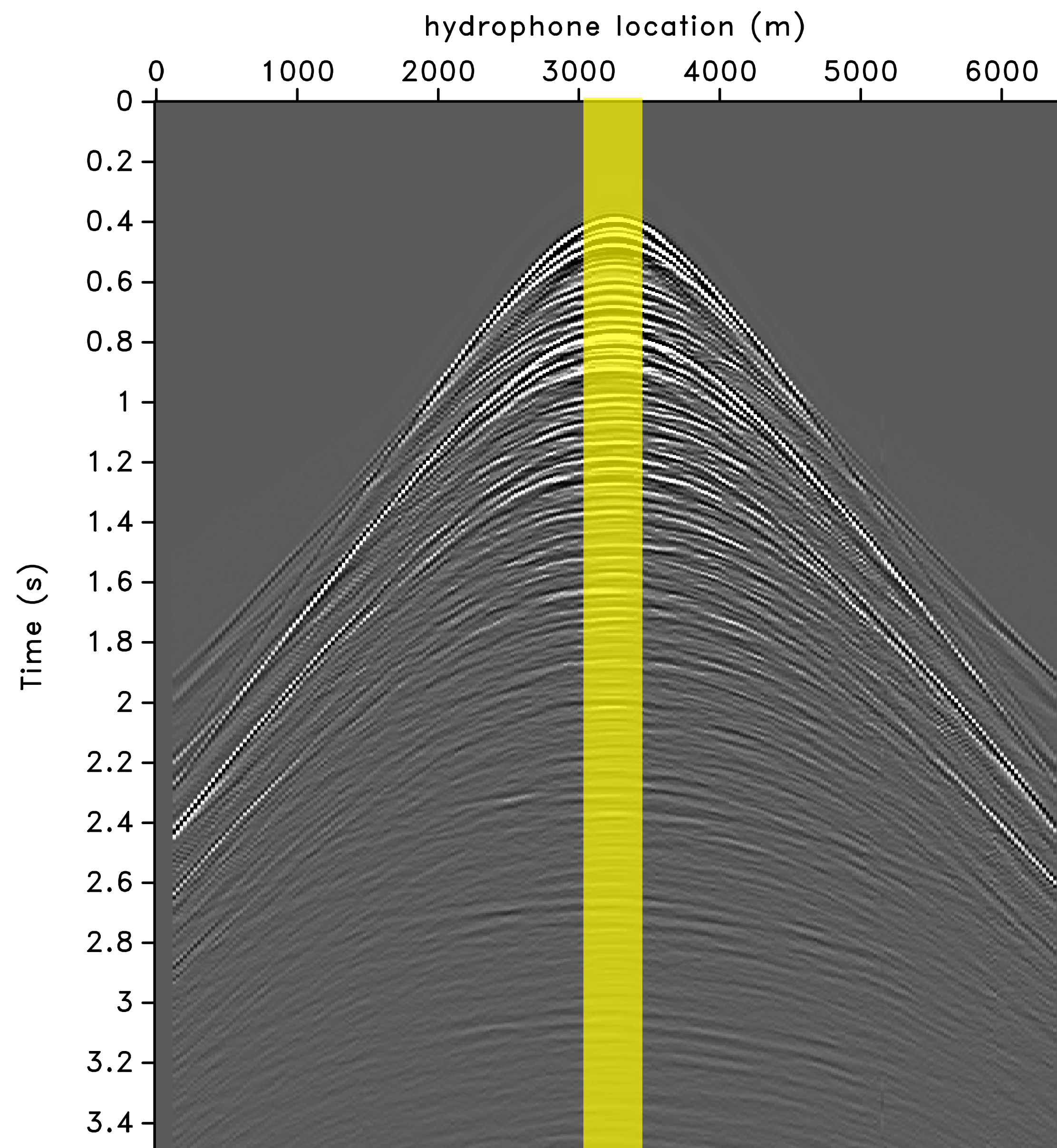
# Trace Mask

Masking operator **K**



# Trace Mask

Bisects wavefield data to unknown/  
uncertain traces  
(i.e., near offset)

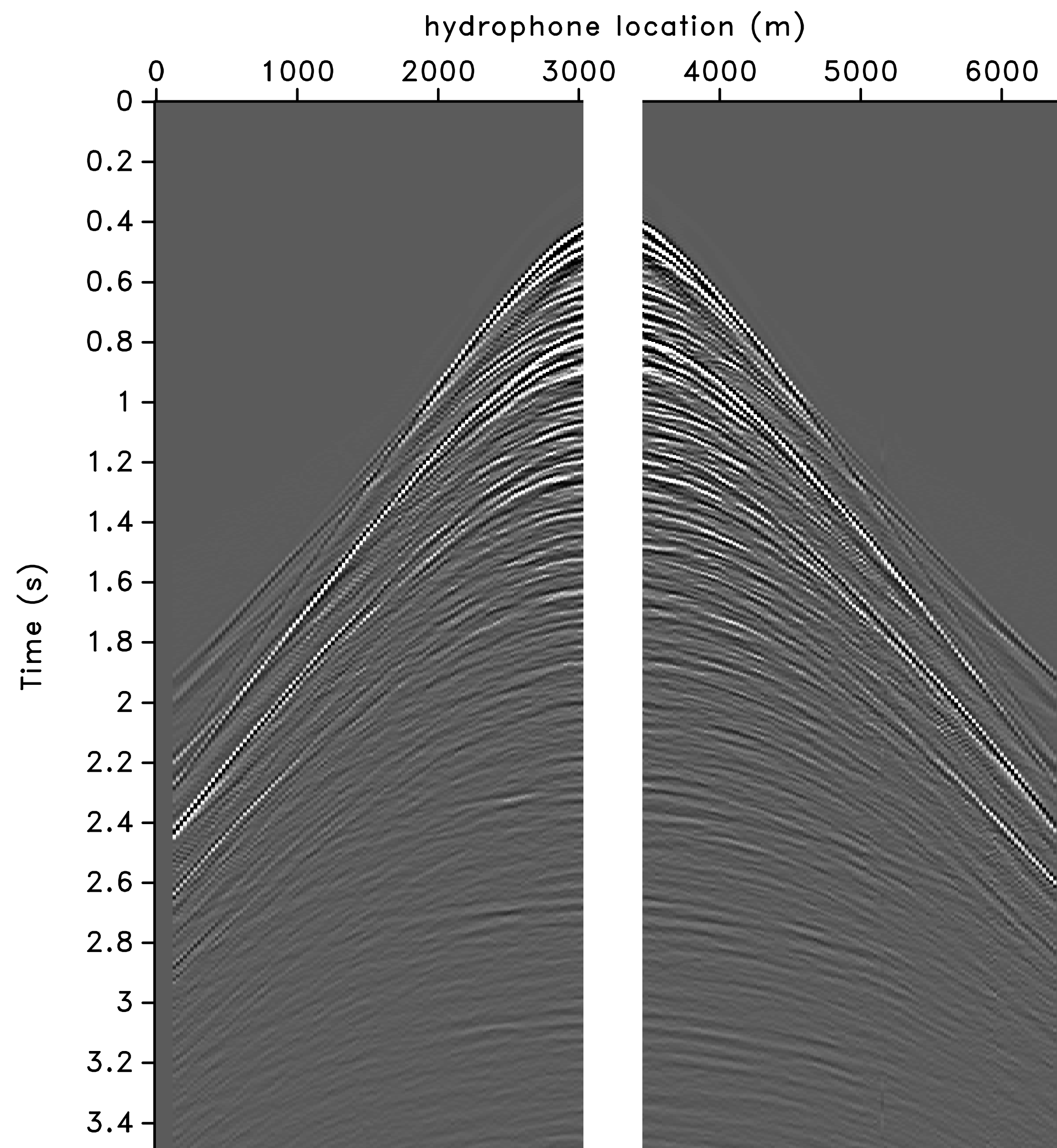


# Trace Mask

Masking operator  $\mathbf{K}$

Time domain:  $\mathbf{Kp}$

Frequency slices:  $\mathbf{K} \circ \mathbf{P}$

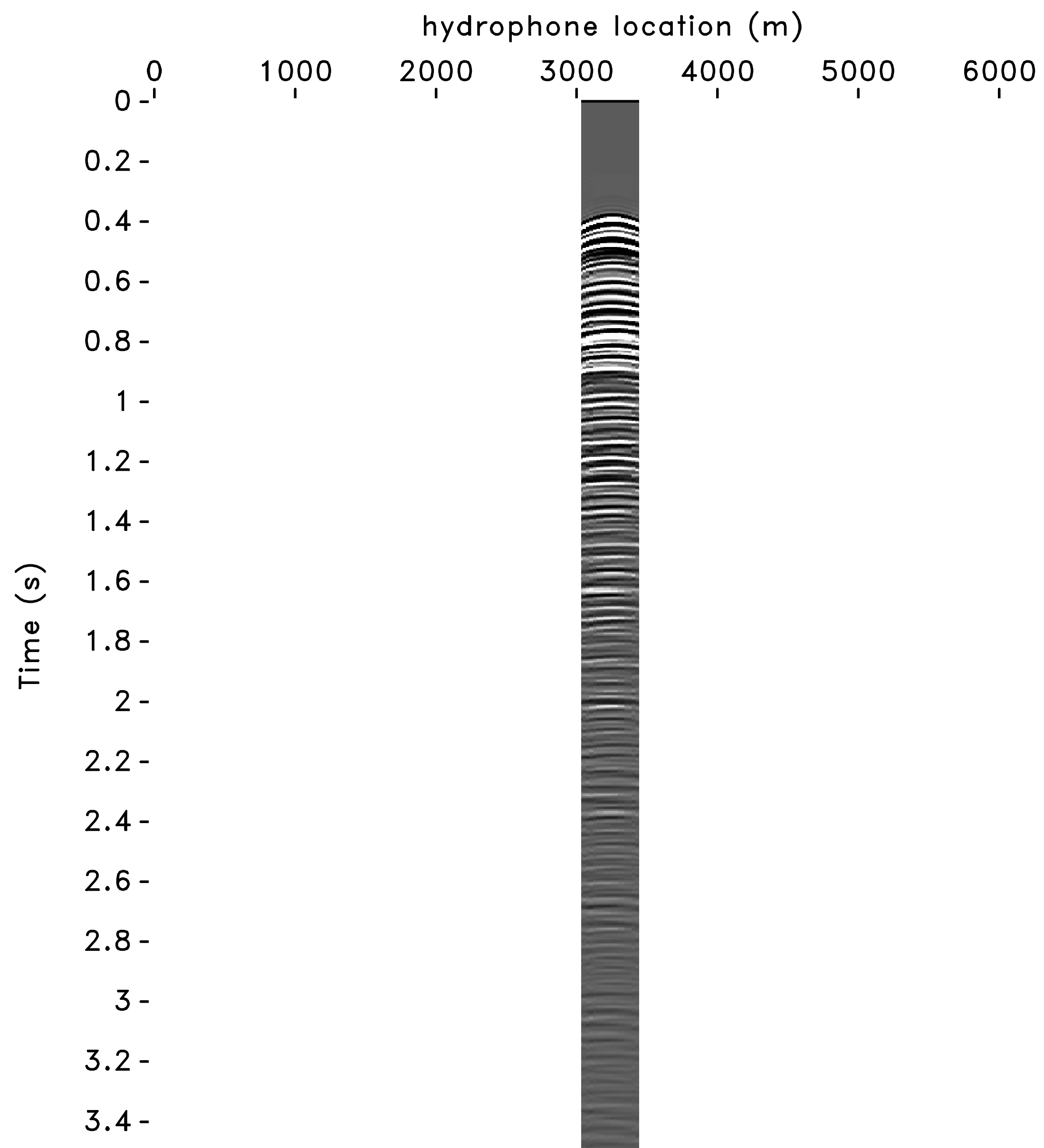


# Trace Mask

Complement of  
Masking operator  $\mathbf{K}_c$

Time domain:  $\mathbf{K}_c \mathbf{p}$

Frequency slices:  $\mathbf{K}_c \circ \mathbf{P}$



## Bisected data variables $\mathbf{P}' + \mathbf{P}'' = \mathbf{P}$

Known data traces:  $\mathbf{P}' := \mathbf{K} \circ \mathbf{P}$

Unknown data traces:  $\mathbf{P}'' := \mathbf{K}_c \circ \mathbf{P}$

## Bisected data variables $\mathbf{P}' + \mathbf{P}'' = \mathbf{P}$

Known data traces:  $\mathbf{P}' := \mathbf{K} \circ \mathbf{P}$

Unknown data traces:  $\mathbf{P}'' := \mathbf{K}_c \circ \mathbf{P}$   
 $= \mathbf{K}_c \circ (\mathbf{GQ} + \mathbf{RGP}' + \mathbf{RGP}'')$



## Bisected data variables $P' + P'' = P$

Known data traces:  $P' := K \circ P$

Unknown data traces:  $P'' := K_c \circ P$   
 $= K_c \circ (GQ + RGP' + RGP'')$

Highly dependent on G

## Bisected data variables $P' + P'' = P$

Known data traces:  $P' := K \circ P$

Unknown data traces:  $P'' := K_c \circ P$

$$= K_c \circ (GQ + RGP' + RGP'')$$

Recursively defined

## Modify the modeling operator

$$\mathcal{M}(\mathbf{G}, \mathbf{Q}; \mathbf{P}') = \mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}' + \mathbf{R}\mathbf{G}\mathbf{P}''$$

## Modify the modeling operator

$$\begin{aligned}\widetilde{\mathcal{M}}(\mathbf{G}, \mathbf{Q}; \mathbf{P}') &= \mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}' \\ &\quad + \mathbf{K} \circ \mathbf{R}\mathbf{G}\mathbf{K}_c \circ (\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}') \\ &\quad + \mathcal{O}(\mathbf{G}^3)\end{aligned}$$

## Modify the modeling operator

$$\widetilde{\mathcal{M}}(\mathbf{G}, \mathbf{Q}; \mathbf{P}') = \mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}'$$

$$\begin{aligned} \text{2nd Order autoconvolution term} &+ \mathbf{K} \circ \mathbf{R}\mathbf{G}\mathbf{K}_c \circ (\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}') \\ &+ \mathcal{O}(\mathbf{G}^3) \end{aligned}$$

## Modify the modeling operator

$$\begin{aligned}\widetilde{\mathcal{M}}(\mathbf{G}, \mathbf{Q}; \mathbf{P}') = & \mathbf{K} \circ [\mathbf{GQ} + \mathbf{RGP}' \\ & + \mathbf{RGK}_c \circ (\mathbf{GQ} + \mathbf{RGP}') \\ & + \mathcal{O}(\mathbf{G}^3)]\end{aligned}$$

## Modify the modeling operator

$$\begin{aligned}
 \widetilde{\mathcal{M}}(\mathbf{G}, \mathbf{Q}; \mathbf{P}') &= \mathbf{K} \circ [\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}'] \\
 \text{2nd Order autoconvolution term} &+ \mathbf{R}\mathbf{G}\mathbf{K}_c \circ (\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}') \\
 \text{3rd Order autoconvolution term} &+ \mathbf{R}\mathbf{G}\mathbf{K}_c \circ (\mathbf{R}\mathbf{G}\mathbf{K}_c \circ (\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}')) \\
 &+ \mathcal{O}(\mathbf{G}^4)] \\
 &:= \mathbf{K} \circ \sum_{n=0}^{\infty} (\mathbf{R}\mathbf{G}\mathbf{K}_c \circ)^n (\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}').
 \end{aligned}$$

## Convergent sum

$$\begin{aligned}\mathbf{K} \circ \mathbf{P} &= \mathbf{K} \circ \sum_{n=0}^{\infty} (\mathbf{R} \mathbf{G} \mathbf{K}_{c \circ})^n (\mathbf{G} \mathbf{Q} + \mathbf{R} \mathbf{G} \mathbf{P}') \\ &= \mathbf{K} \circ (\mathbf{I} - \mathbf{R} \mathbf{G} \mathbf{K}_{c \circ})^{-1} (\mathbf{G} \mathbf{Q} + \mathbf{R} \mathbf{G} \mathbf{P}')\end{aligned}$$

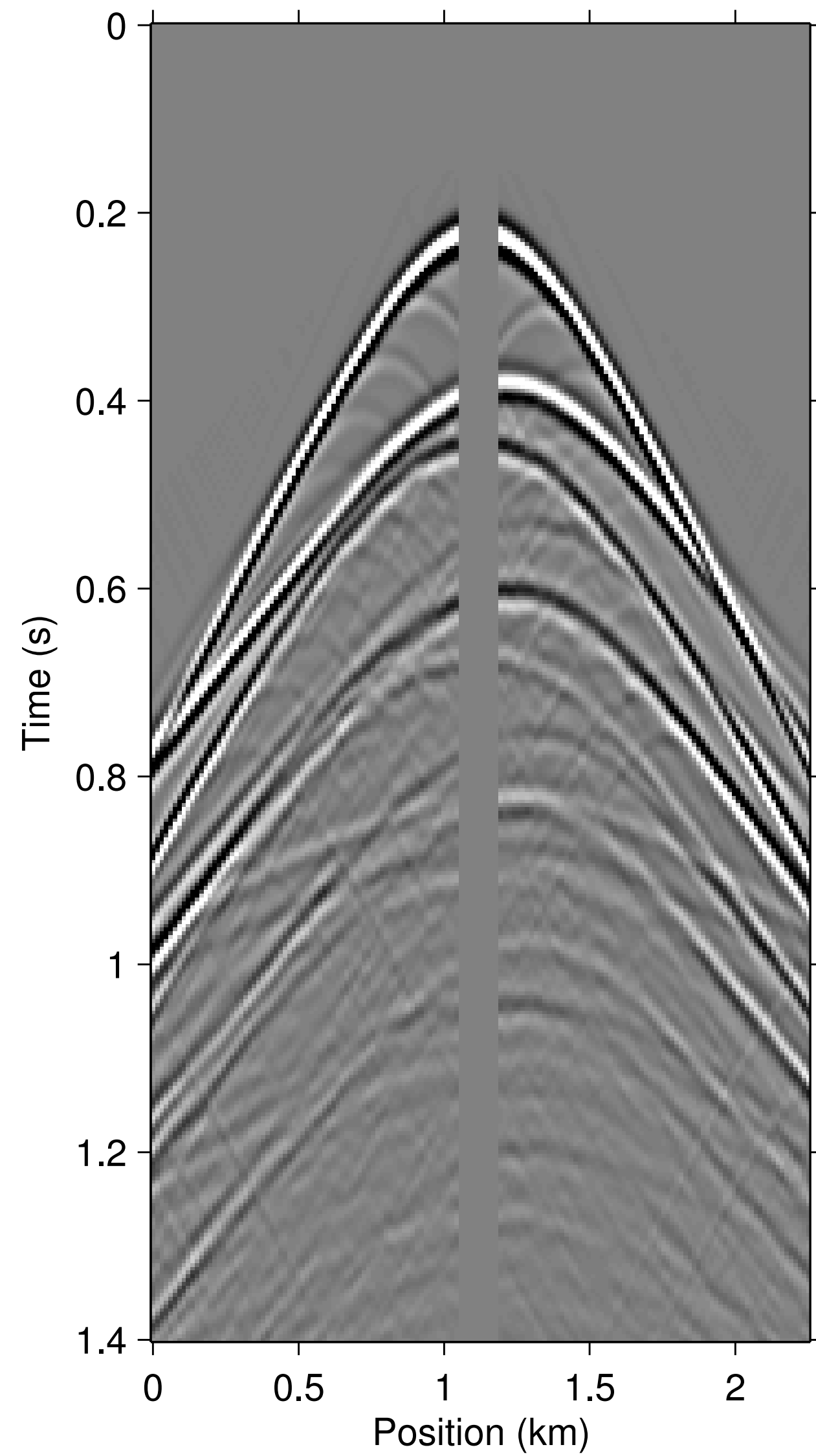


## Convergent sum

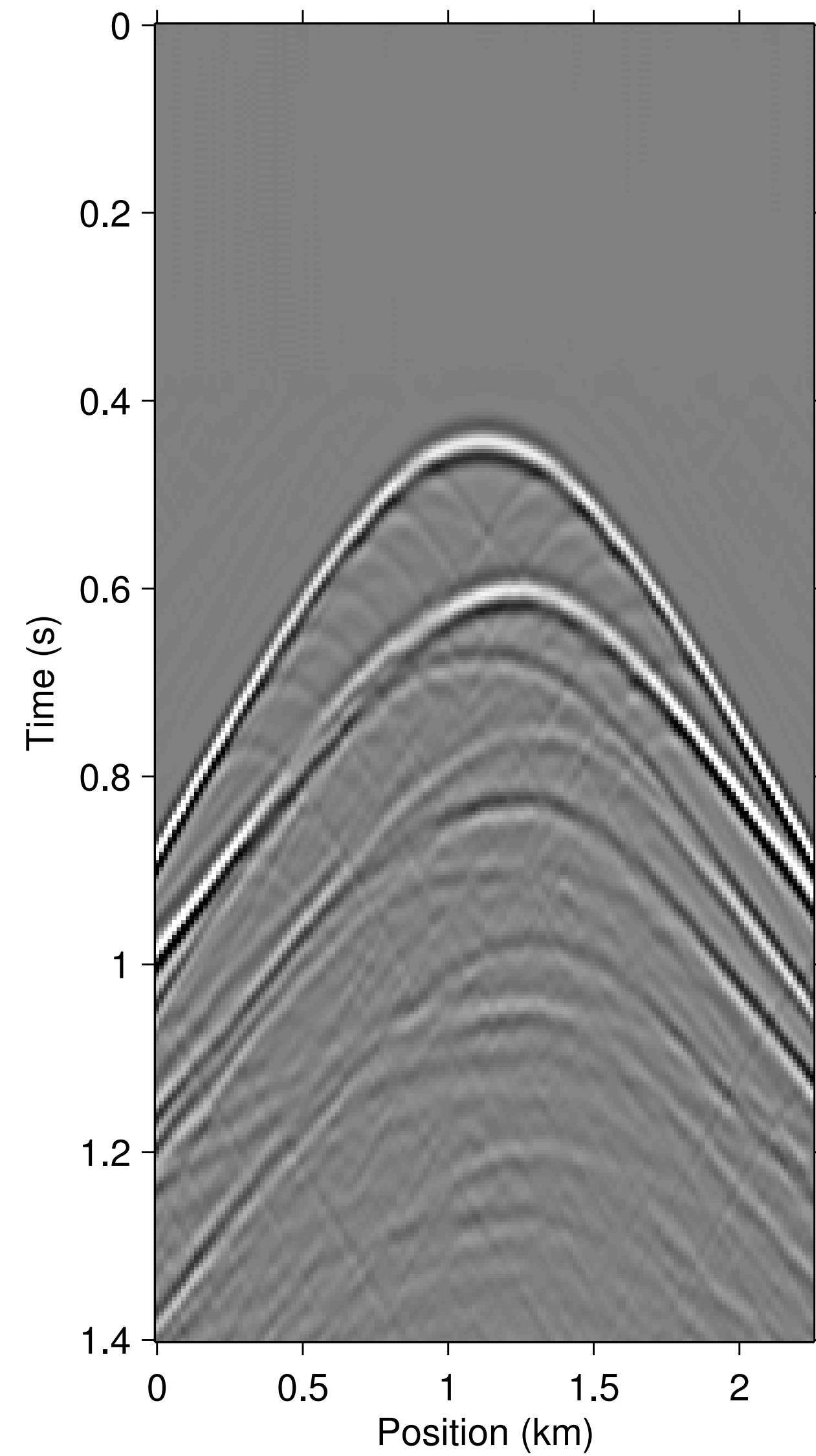
$$\begin{aligned}\mathbf{K} \circ \mathbf{P} &= \mathbf{K} \circ \sum_{n=0}^{\infty} (\mathbf{R} \mathbf{G} \mathbf{K}_{c \circ})^n (\mathbf{G} \mathbf{Q} + \mathbf{R} \mathbf{G} \mathbf{P}') \\ &= \mathbf{K} \circ (\mathbf{I} - \mathbf{R} \mathbf{G} \mathbf{K}_{c \circ})^{-1} (\mathbf{G} \mathbf{Q} + \mathbf{R} \mathbf{G} \mathbf{P}')\end{aligned}$$

Verifies the validity of the expression

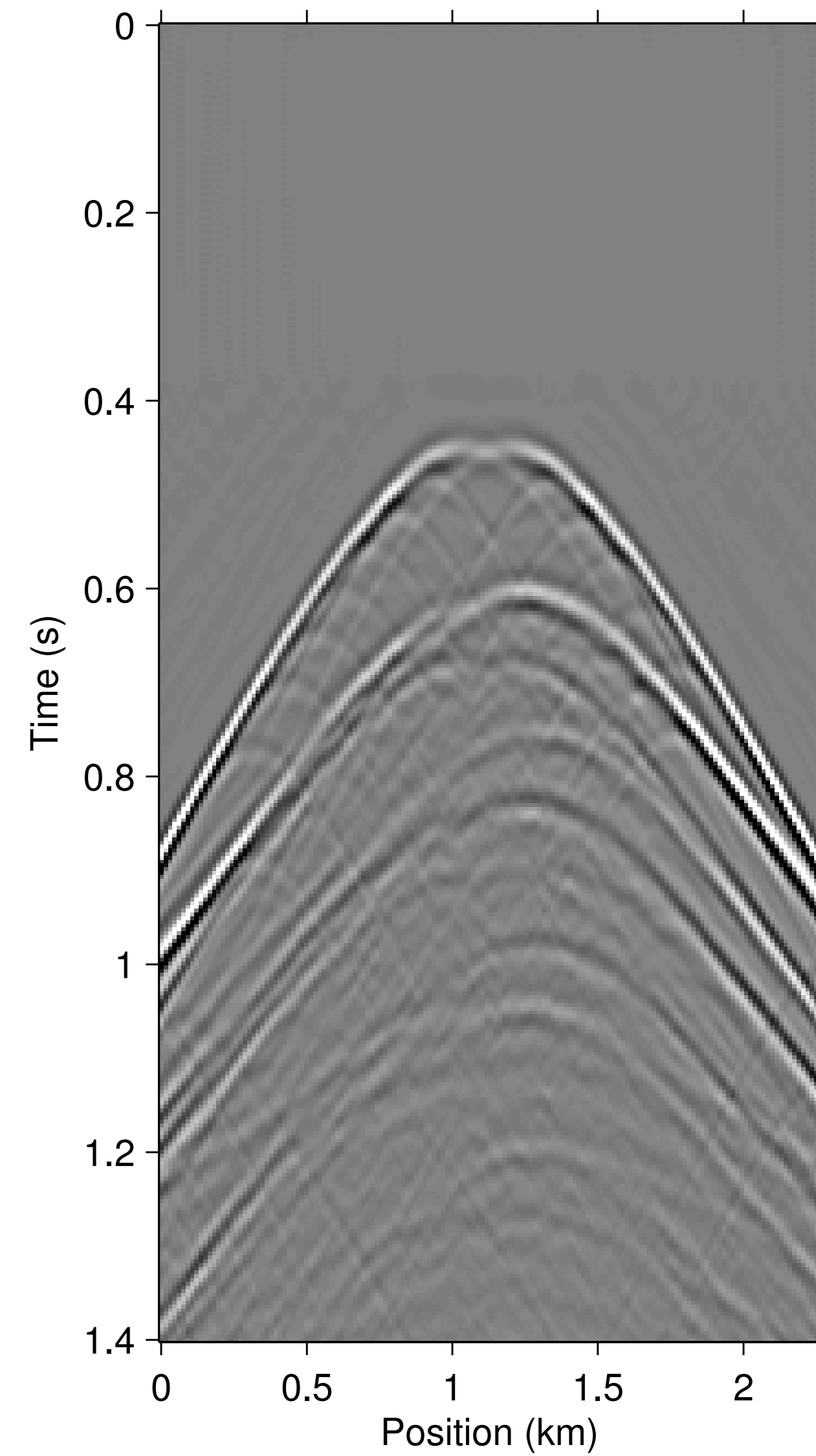
What these terms look like



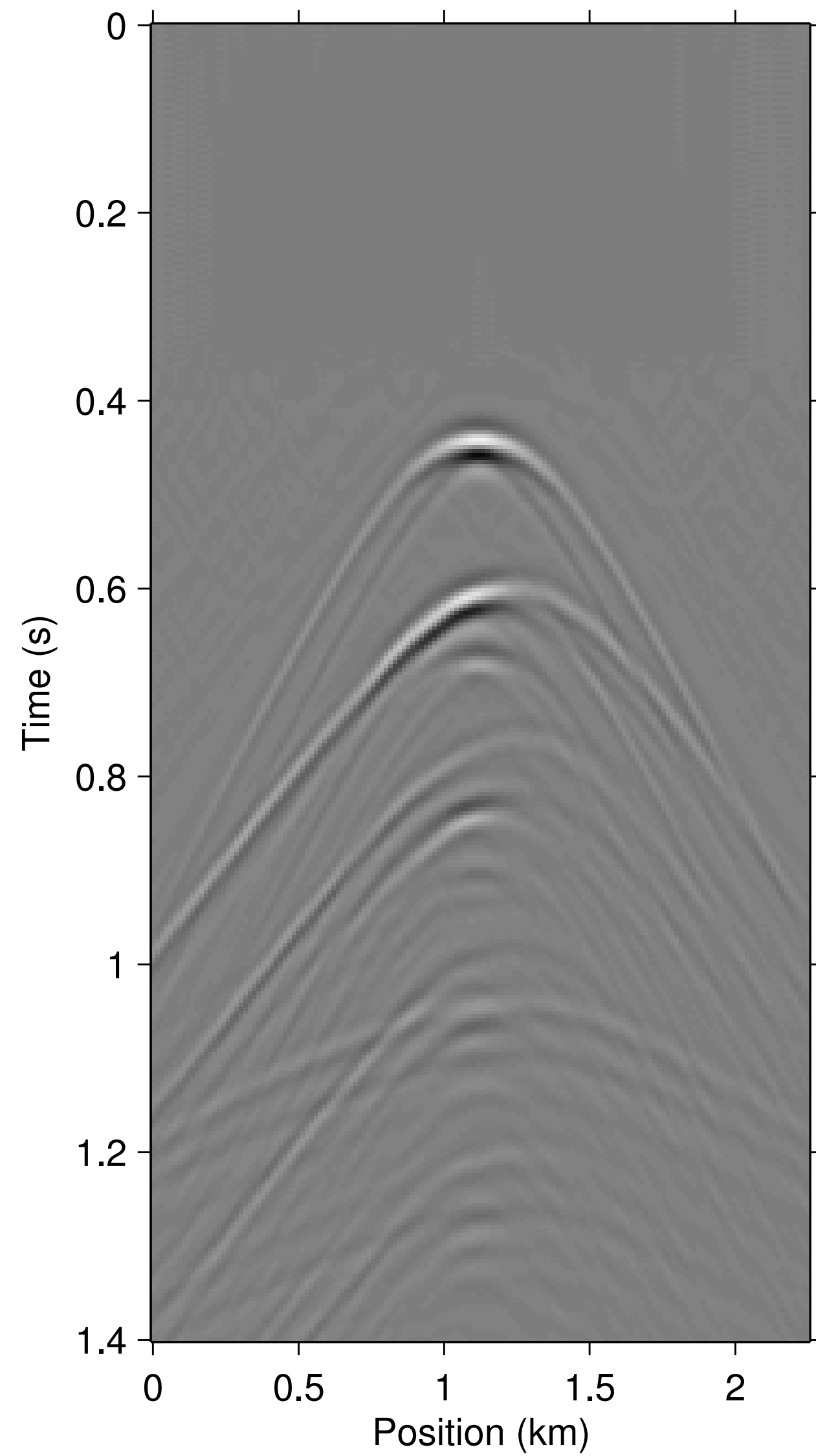
**Data with missing traces  $P'$**



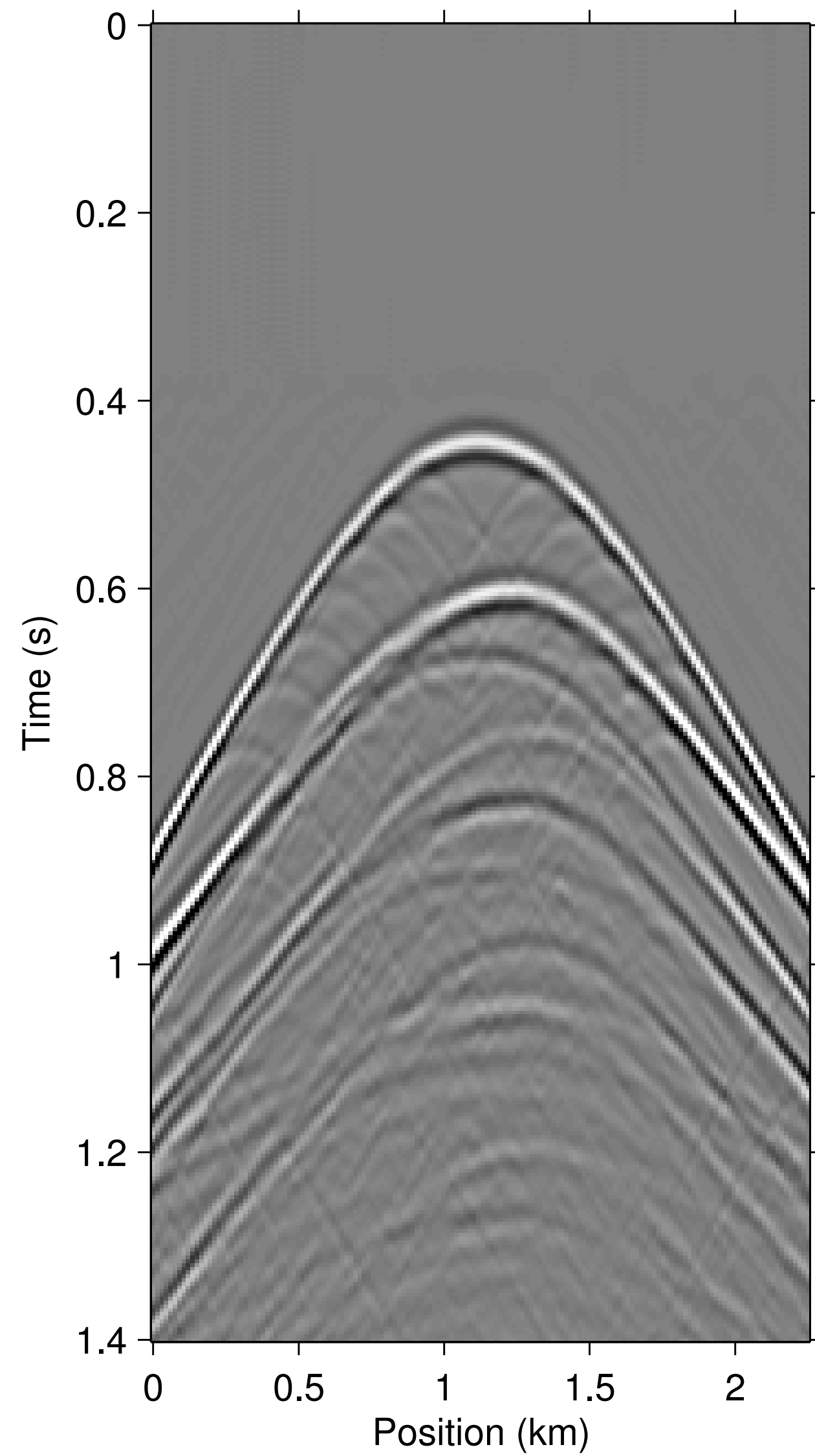
**Exact multiples**



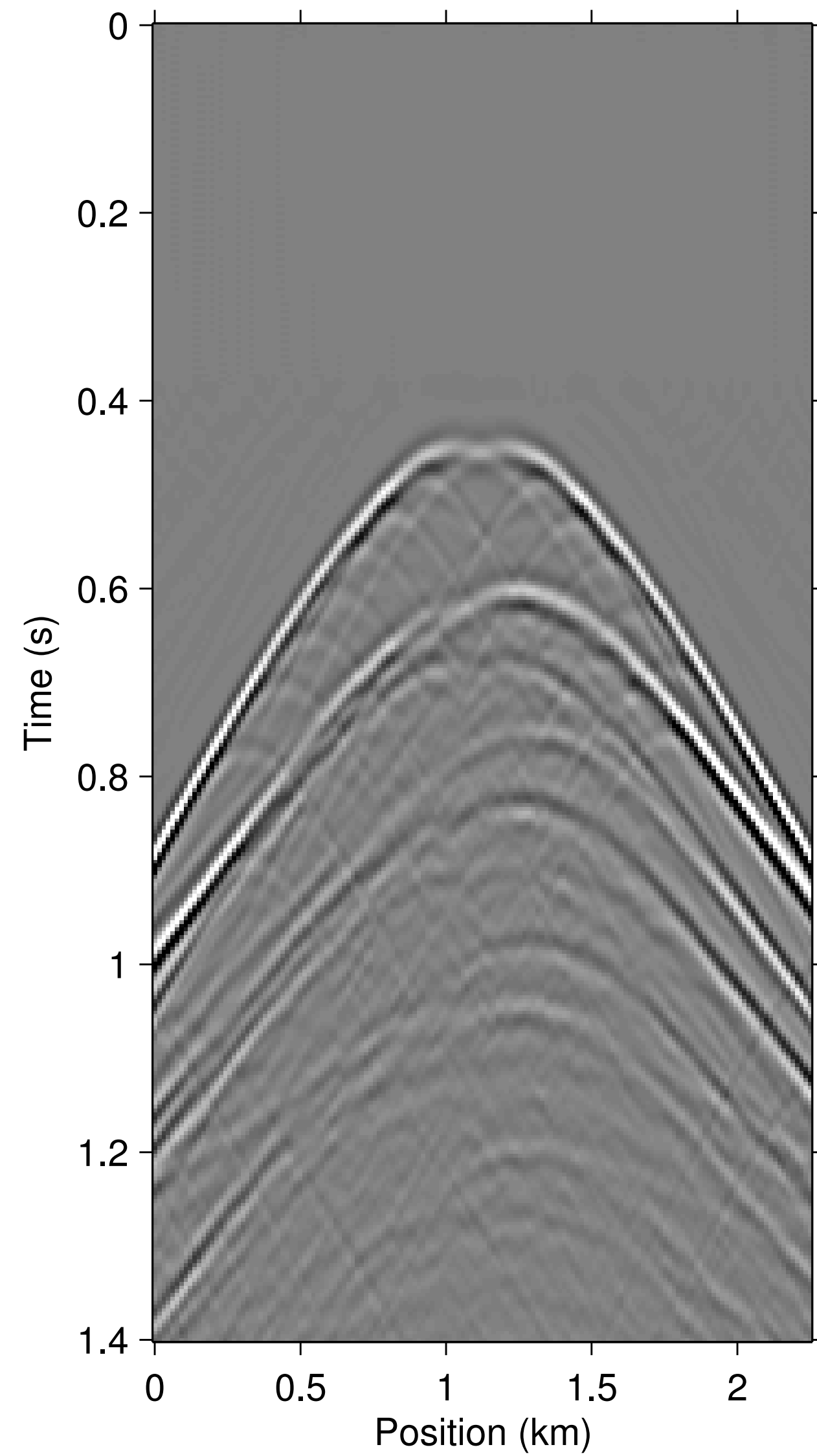
**$-GP'$**



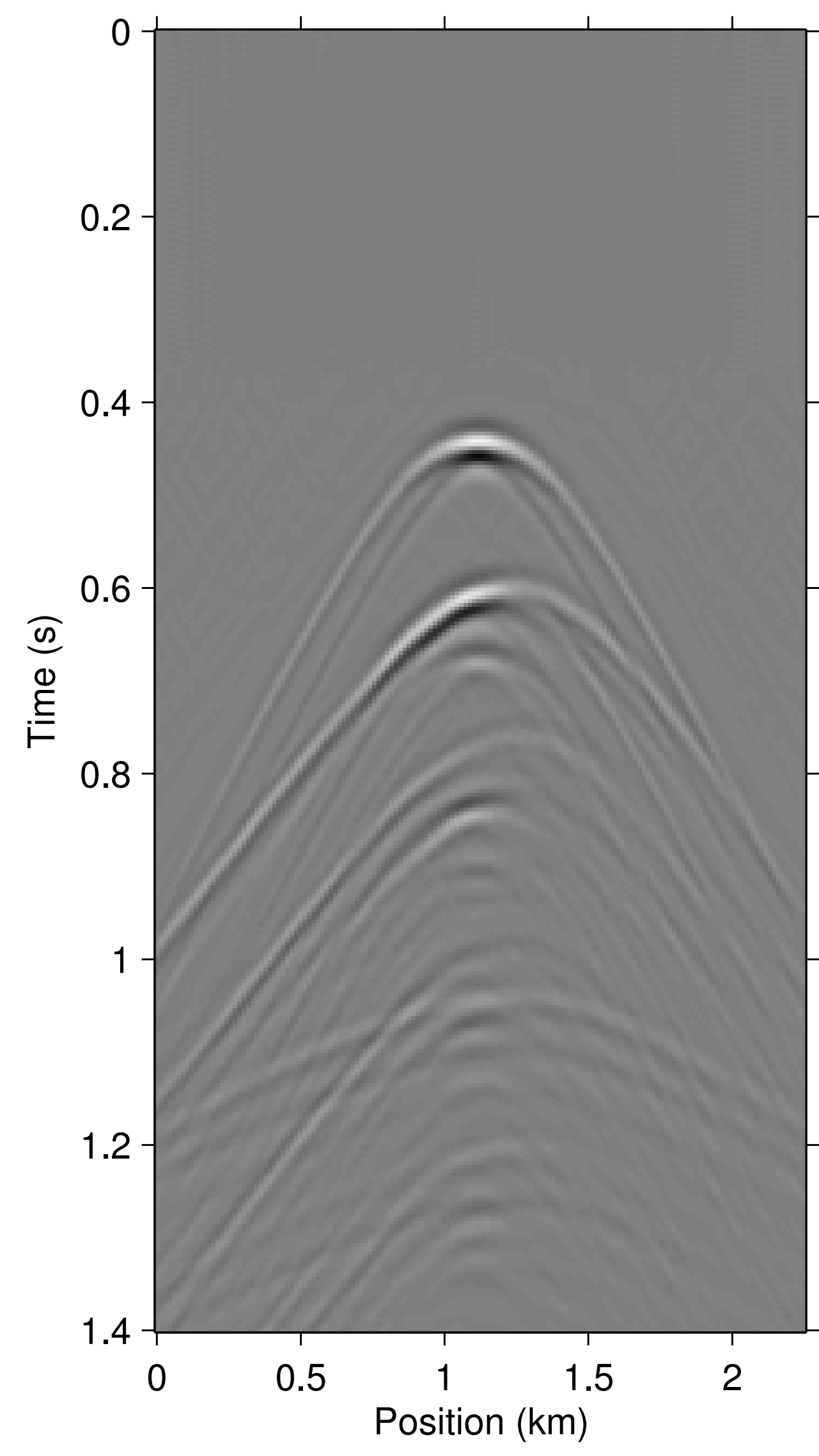
**Missing contributions**



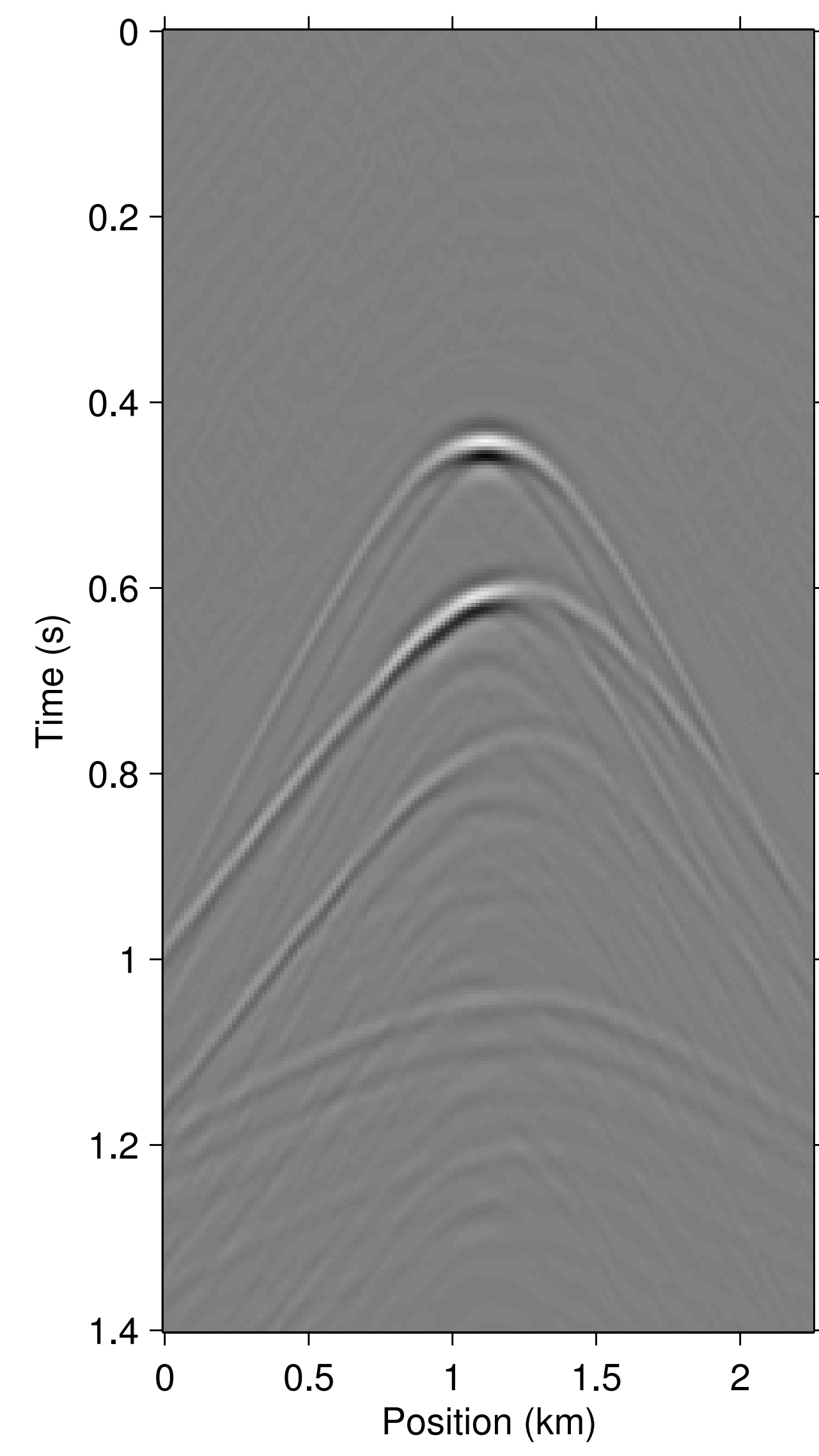
**Exact multiples**



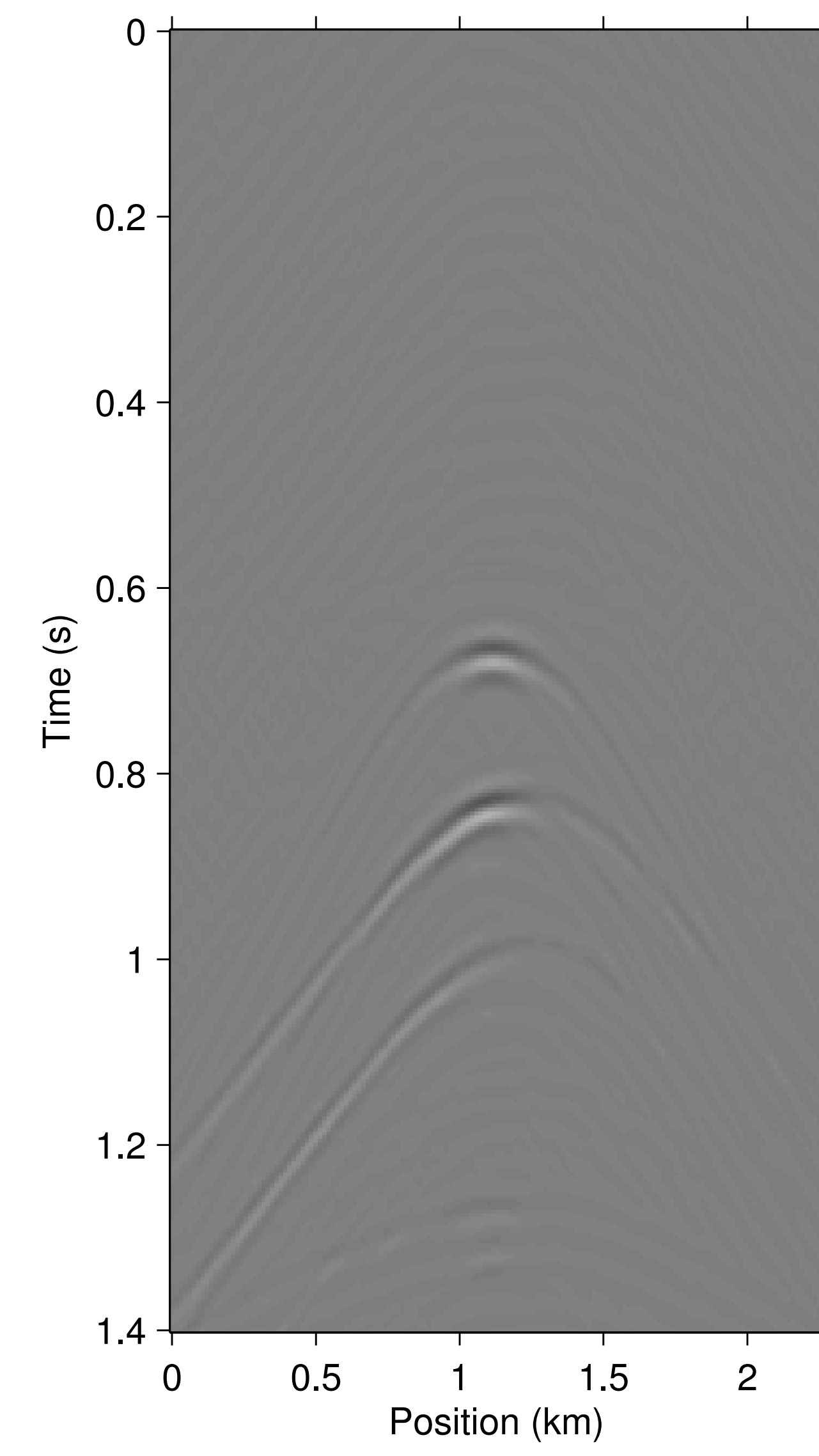
**-GP\'**



**Missing contributions**



**2nd order term**



**3rd order term**

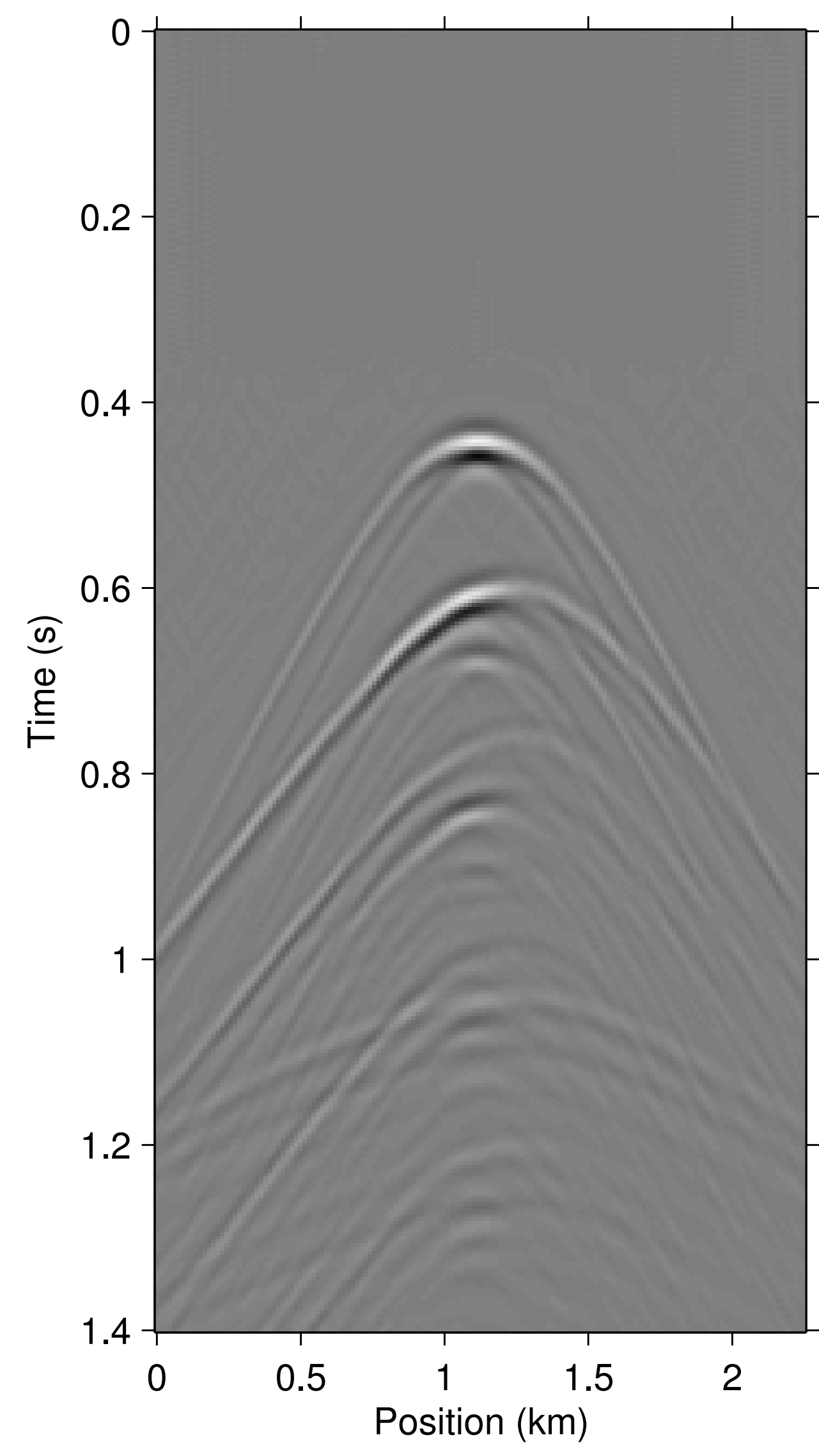
## Modify the modeling operator

$$\widetilde{\mathcal{M}}(\mathbf{G}, \mathbf{Q}; \mathbf{P}') = \mathbf{K} \circ [\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}']$$

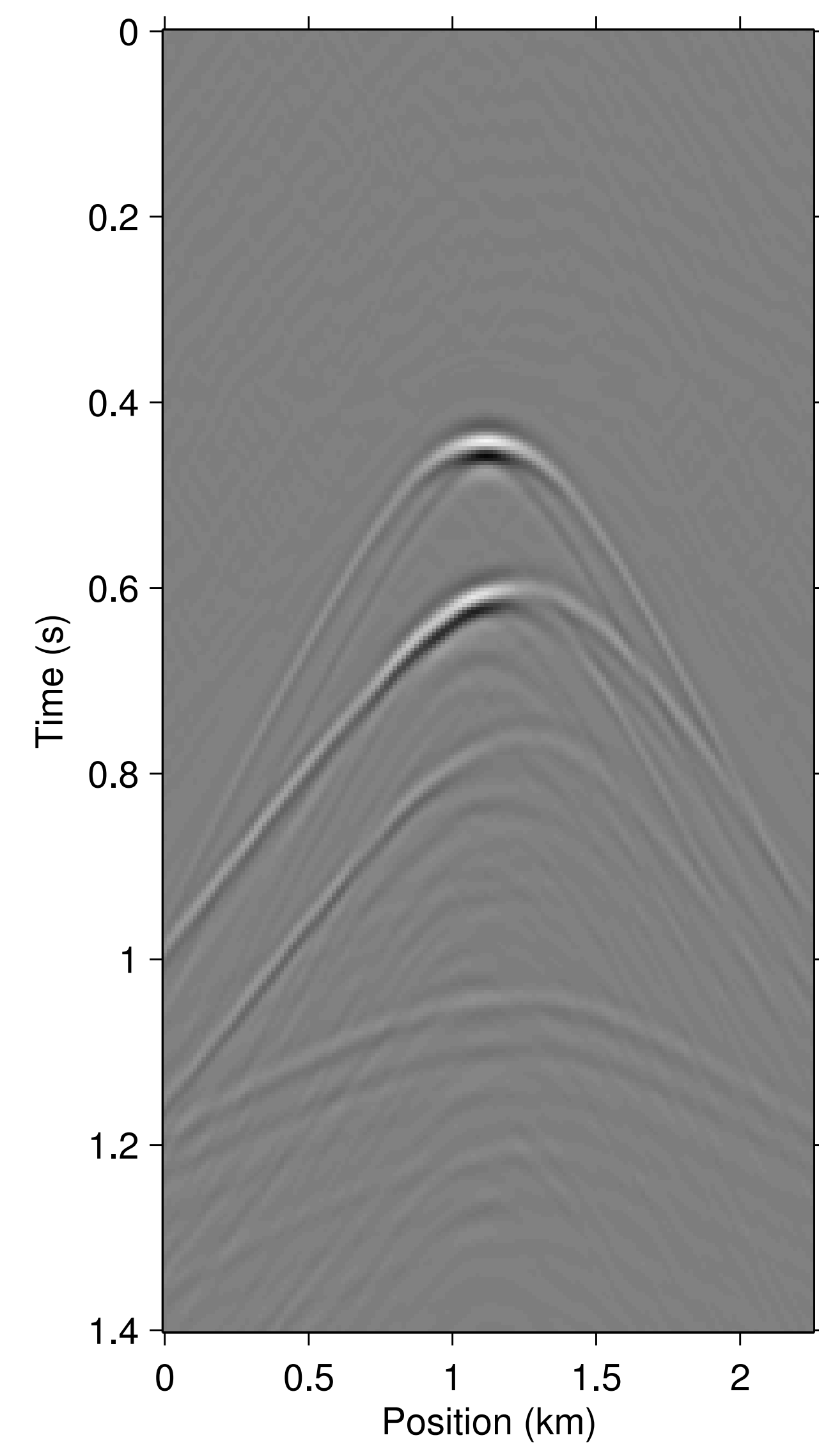
2nd Order autoconvolution term  $+ \mathbf{R}\mathbf{G}\mathbf{K}_c \circ (\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}')$

3rd Order autoconvolution term  $+ \mathbf{R}\mathbf{G}\mathbf{K}_c \circ (\mathbf{R}\mathbf{G}\mathbf{K}_c \circ (\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}'))$   
 $+ \mathcal{O}(\mathbf{G}^4)]$

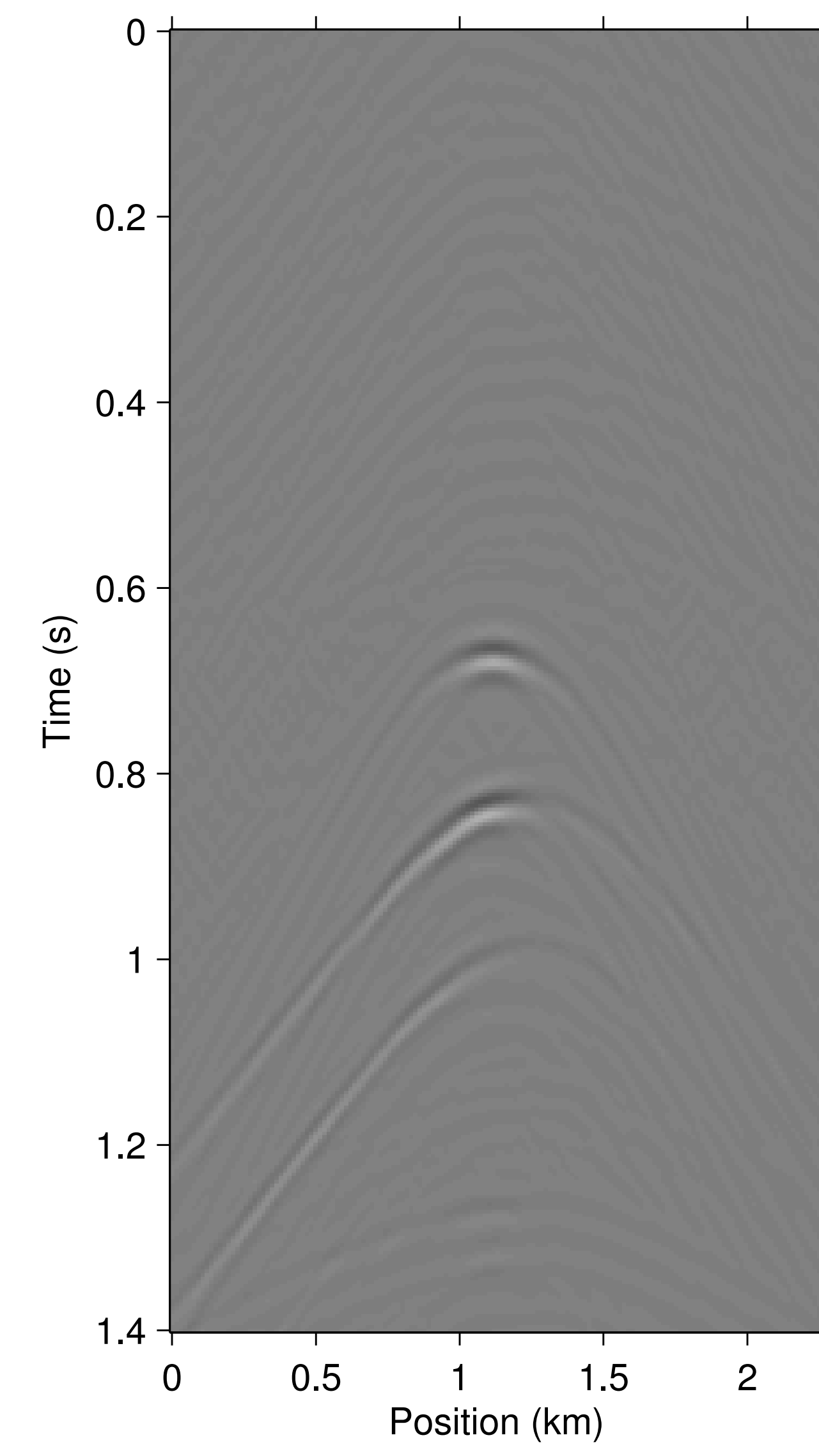
$$:= \mathbf{K} \circ \sum_{n=0}^{\infty} (\mathbf{R}\mathbf{G}\mathbf{K}_c \circ)^n (\mathbf{G}\mathbf{Q} + \mathbf{R}\mathbf{G}\mathbf{P}').$$



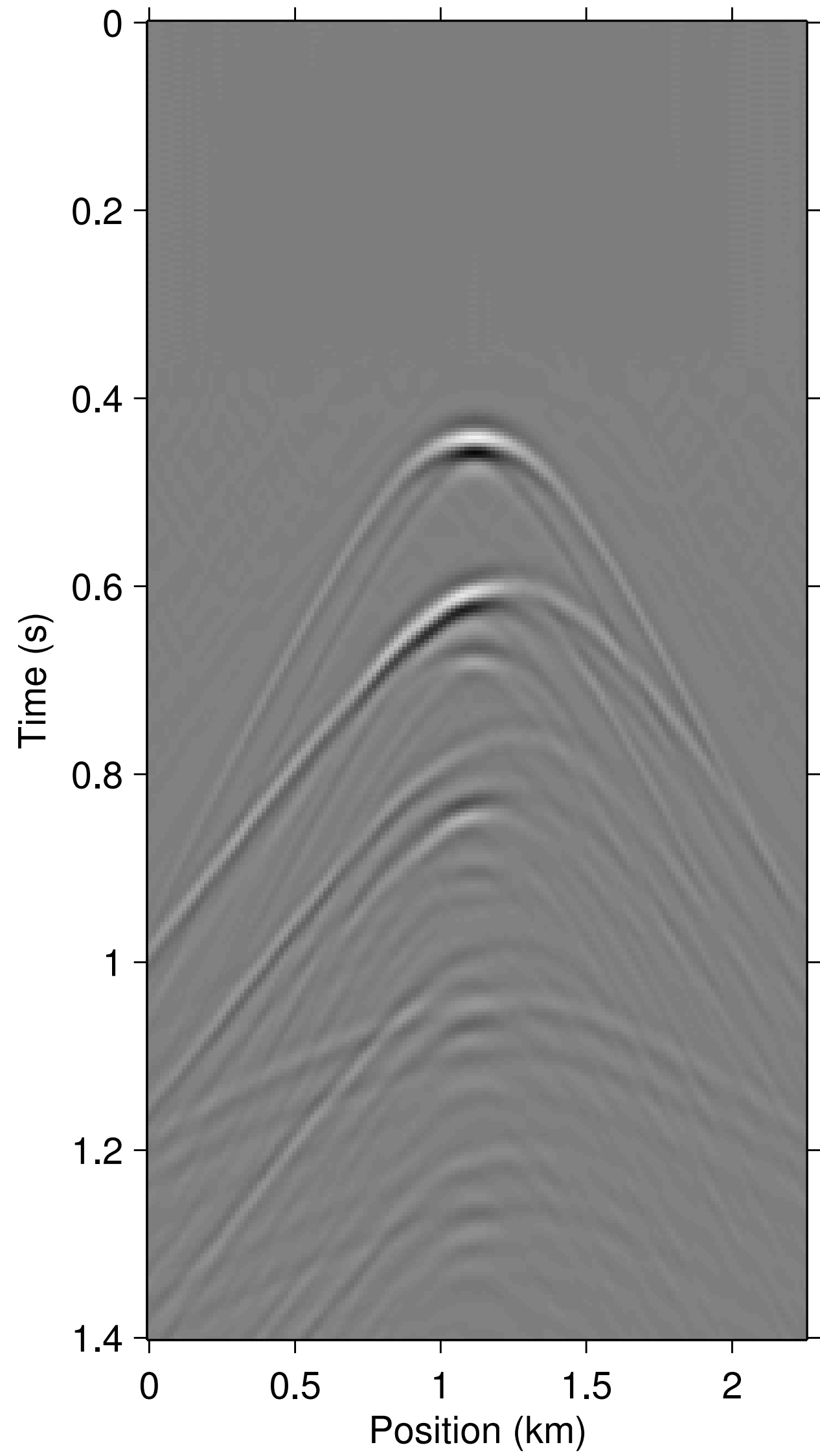
**Missing contributions**



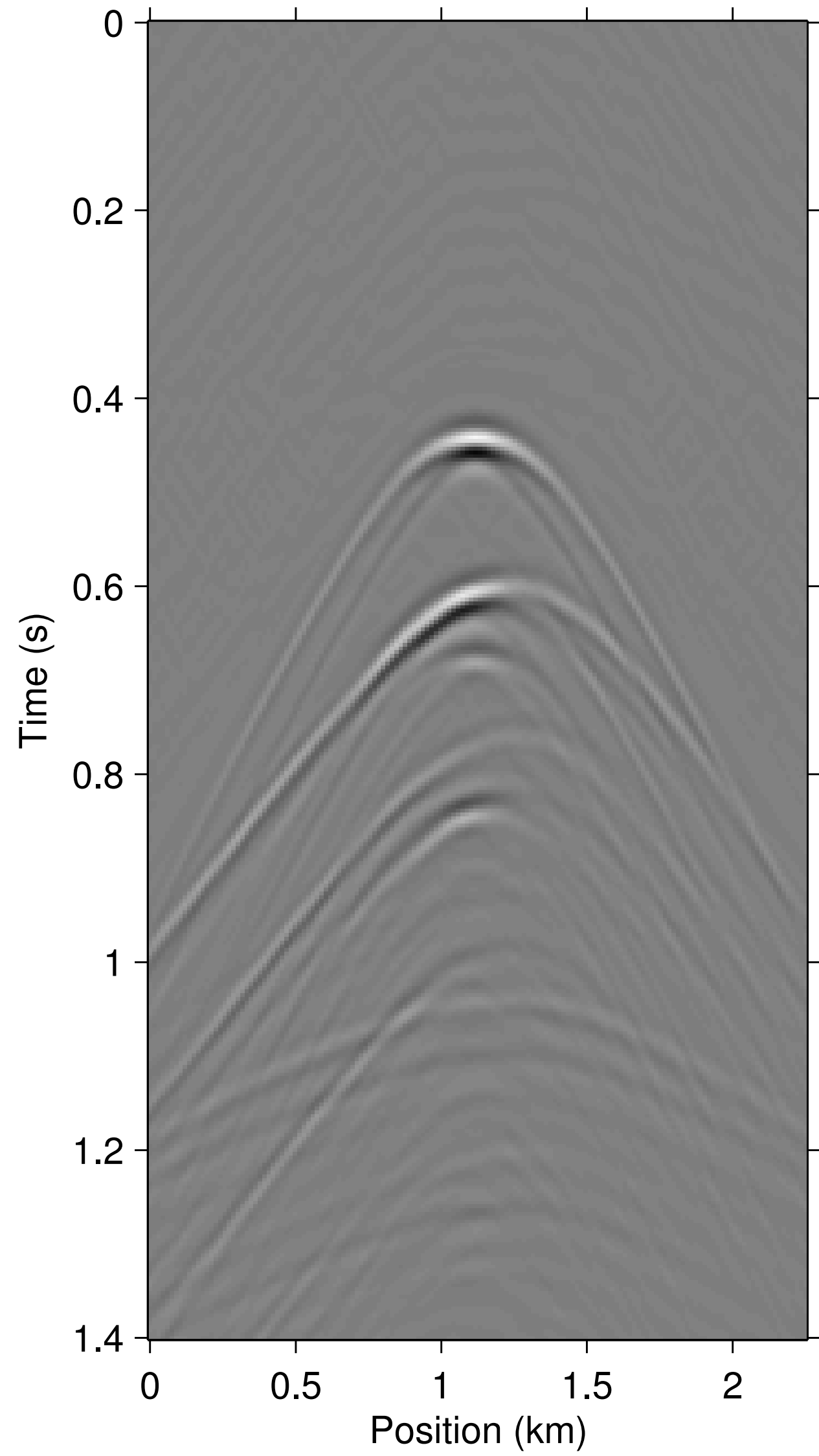
**2nd order term**



**3rd order term**



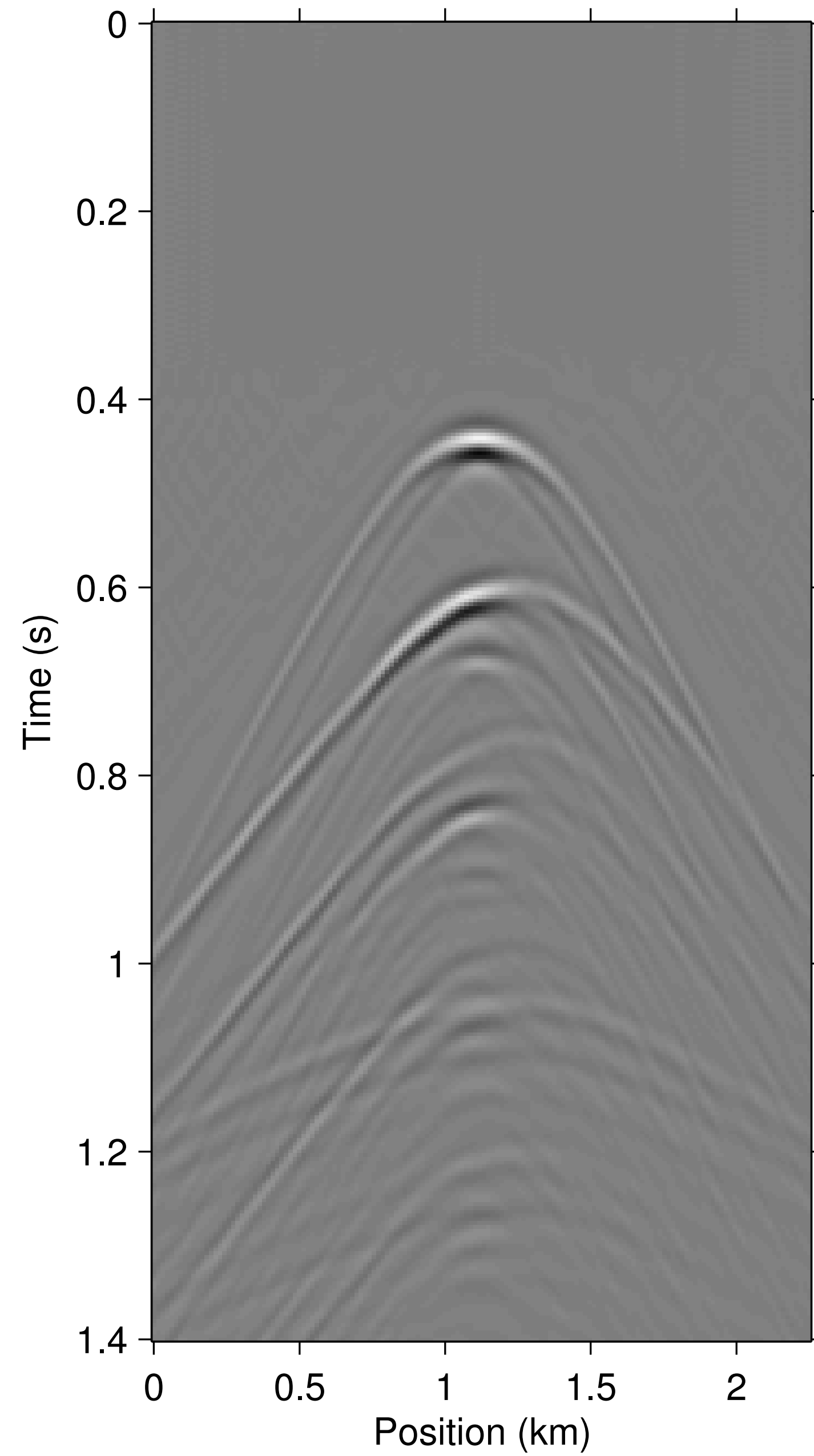
**Missing contributions**



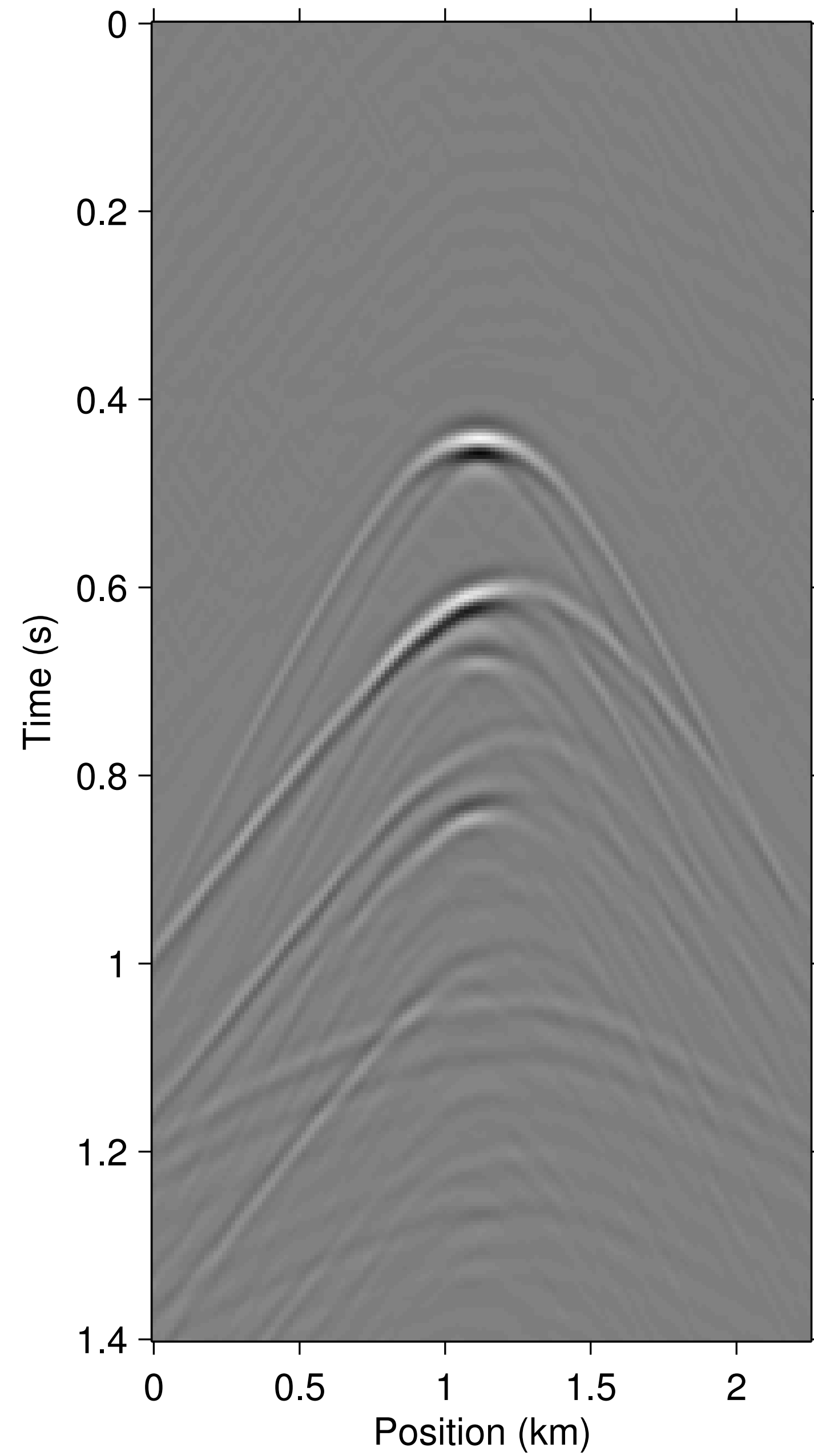
**2nd order term + 3rd order**



# Total missing contrib.



# Modeled with two terms



# Solution strategy

# Robust EPSI

Inverting for unknown data

$$\Delta \mathbf{P}(\mathbf{G}_{k+1}, \mathbf{R}_{k+1}) := -(\mathbf{I} + \mathbf{G}_{k+1})^H (\mathbf{R}_{k+1})$$

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

determine new  $\tau_k$  from the Pareto curve

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

$$\mathbf{q}_{k+1} = \arg \min_{\mathbf{q}} \|\mathbf{p}_k - \mathbf{M}_{g_{k+1}} \mathbf{q}\|_2$$

$$\mathbf{p}_{k+1} = \mathbf{p}_k + \alpha \Delta \mathbf{p}(\mathbf{g}_{k+1}, \mathbf{q}_{k+1}, \mathbf{p}_k)$$

# Robust EPSI

Accounting for unknown data with G

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

determine new  $\tau_k$  from the Pareto curve

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

$$\mathbf{q}_{k+1} = \arg \min_{\mathbf{q}} \|\mathbf{p} - \widetilde{\mathbf{M}}_{g_{k+1}} \mathbf{q}\|_2$$

# Strategy 1: Re-linearization

Use  $G$  from previous iter in higher-order terms

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

determine new  $\tau_k$  from the Pareto curve

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

$$\mathbf{q}_{k+1} = \arg \min_{\mathbf{q}} \|\mathbf{p} - \widetilde{\mathbf{M}}_{g_{k+1}} \mathbf{q}\|_2$$

use  $\mathbf{g}_k$  in these operators

## Strategy 2: Modified Gauss-Newton

Obtain Jacobian using  $G$  from previous iter

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

determine new  $\tau_k$  from the Pareto curve

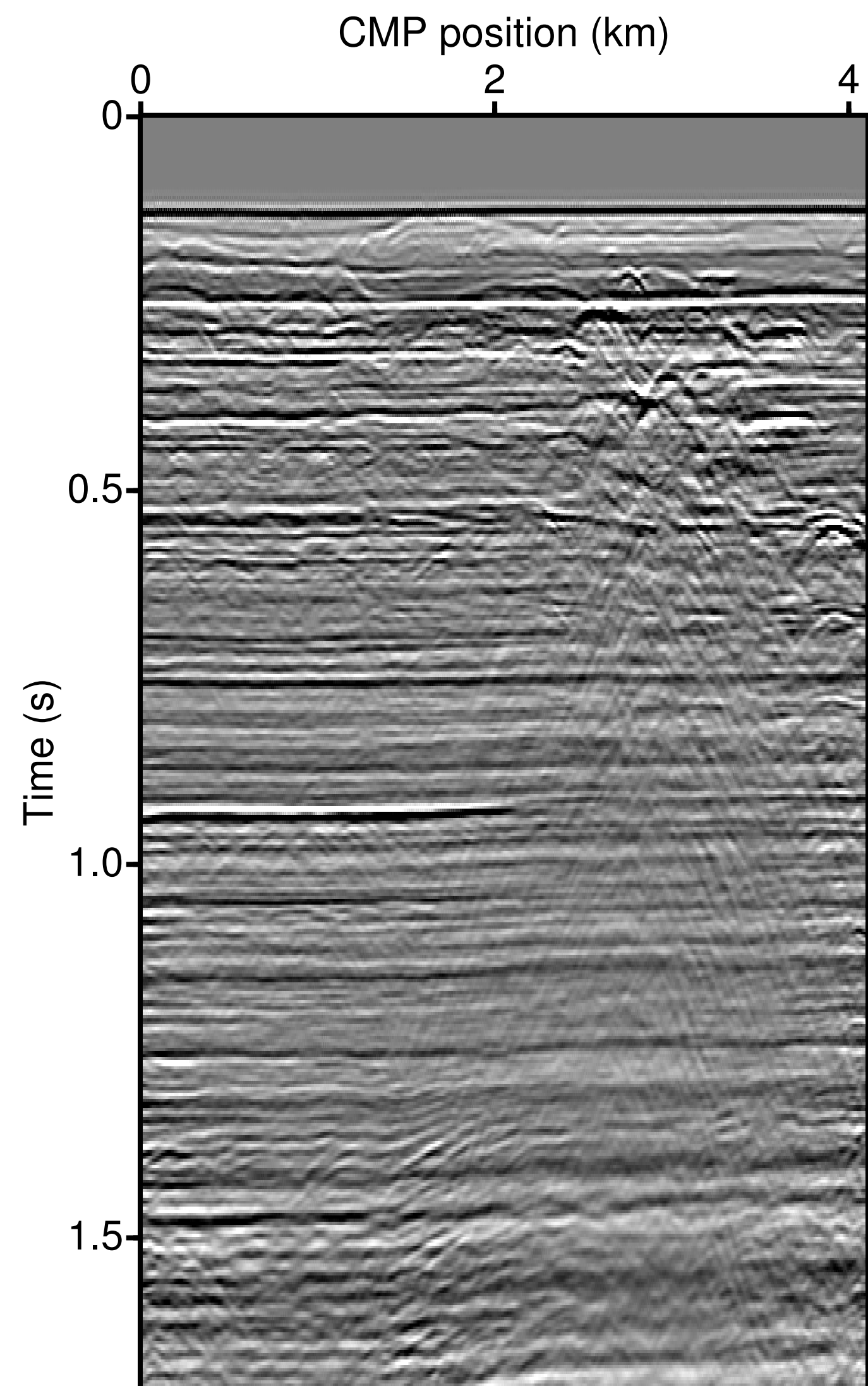
$$\mathbf{g}_{k+1} = \mathbf{g}_k + \arg \min_{\Delta \mathbf{g}} \|\mathbf{r}_k - \partial_{(g_k, q_k)} \widetilde{\mathcal{M}} \Delta \mathbf{g}\|_2 \text{ s.t. } \|\Delta \mathbf{g}\|_1 \leq \tau_k$$

$$\mathbf{q}_{k+1} = \arg \min_{\mathbf{q}} \|\mathbf{p} - \widetilde{\mathbf{M}}_{g_{k+1}} \mathbf{q}\|_2$$

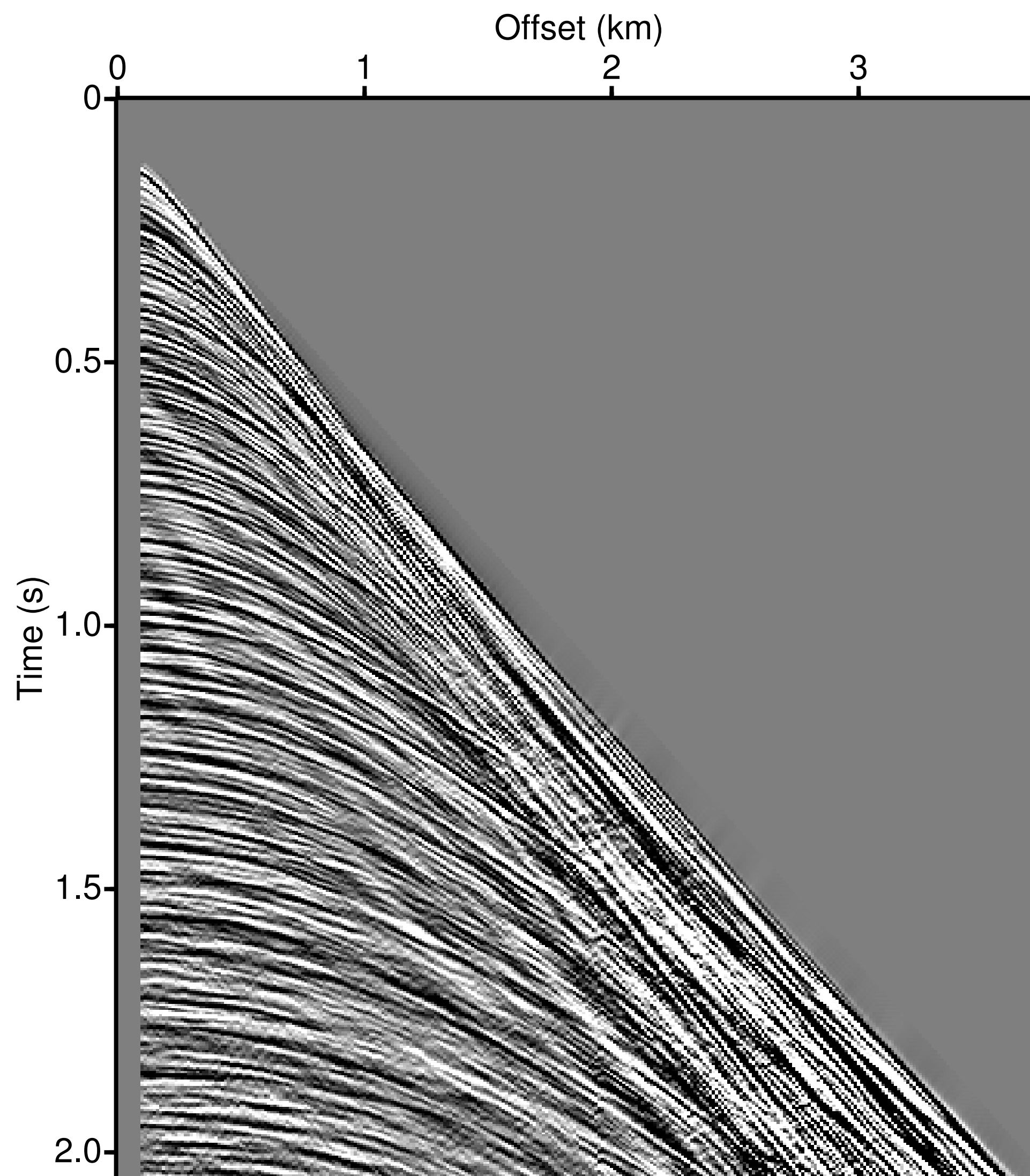
# Field data example

## North Sea dataset



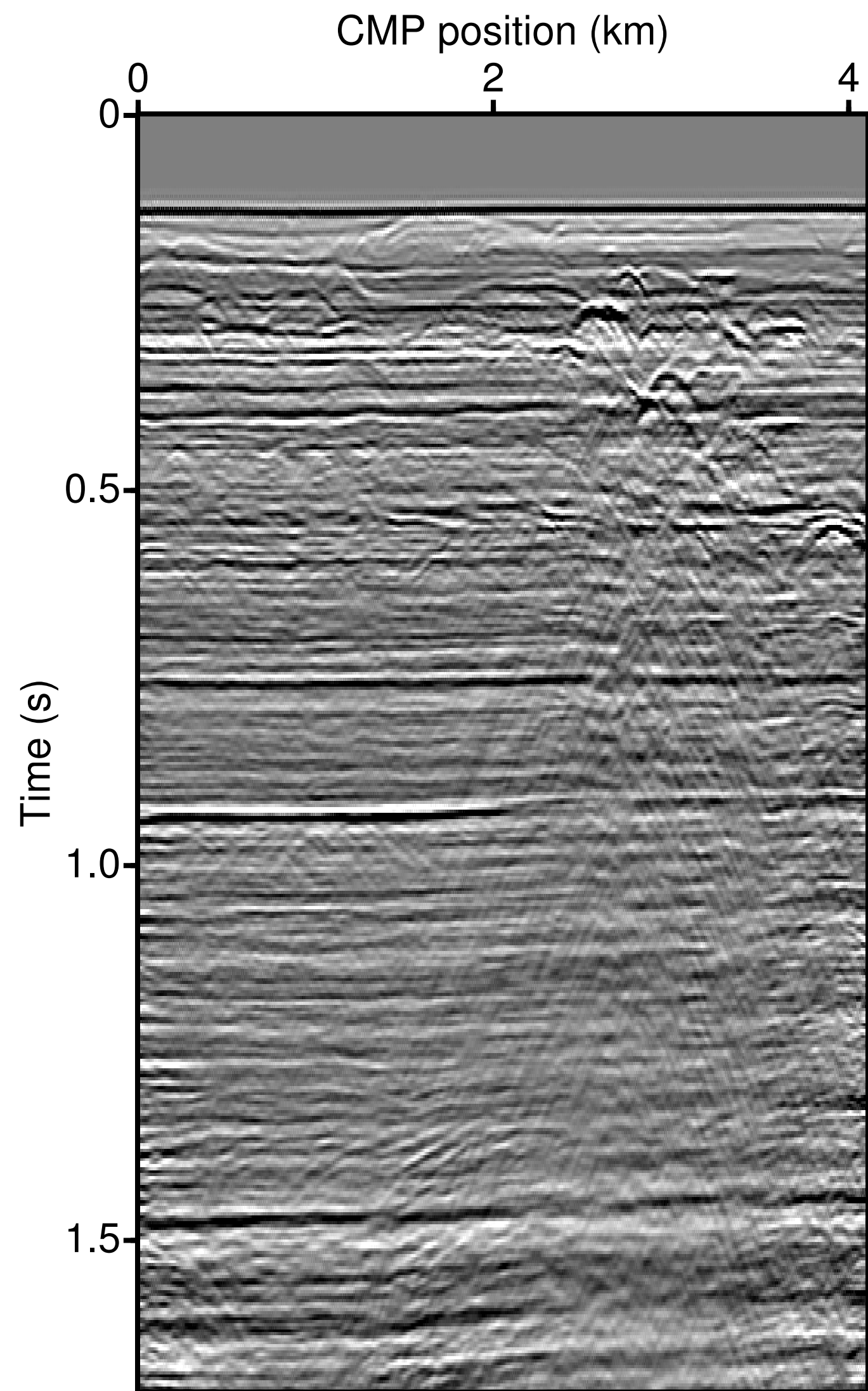


Data

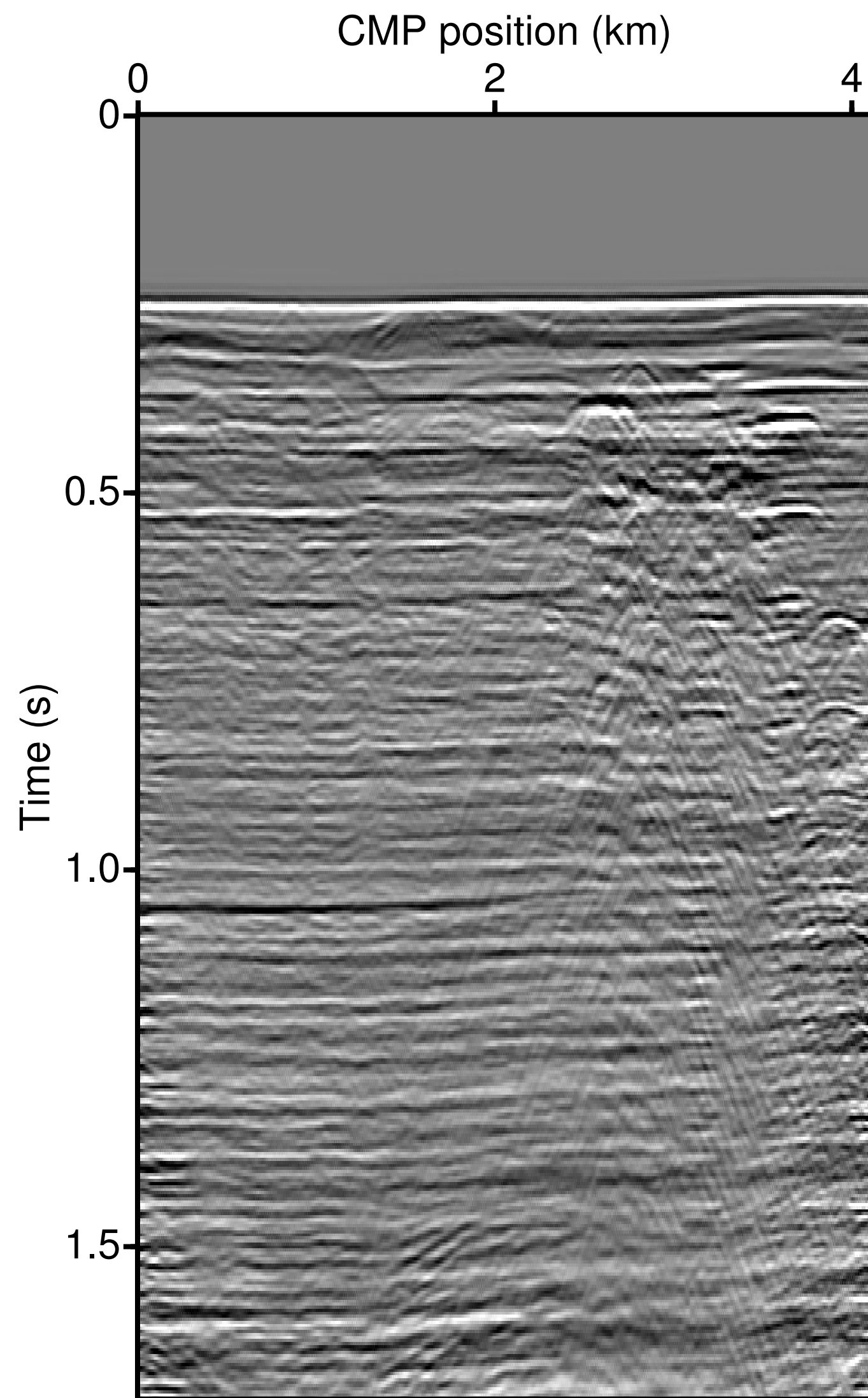


Shot

**North Sea dataset**  
**100m near-offset**  
**regularized to 12.5m dx**  
**and 4km fixed-spread**  
**from streamer**  
**4ms sampling**

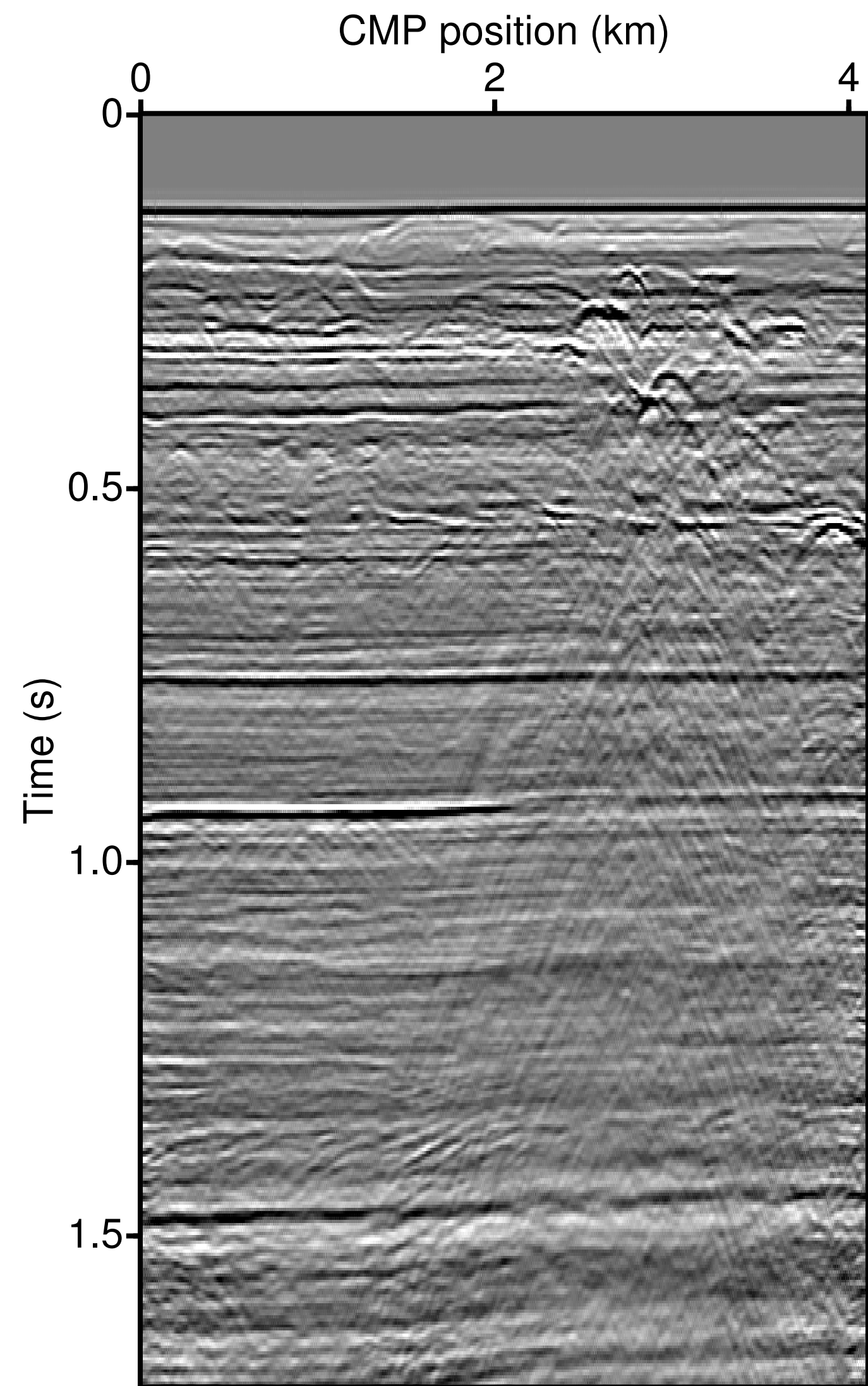


Conservative primary

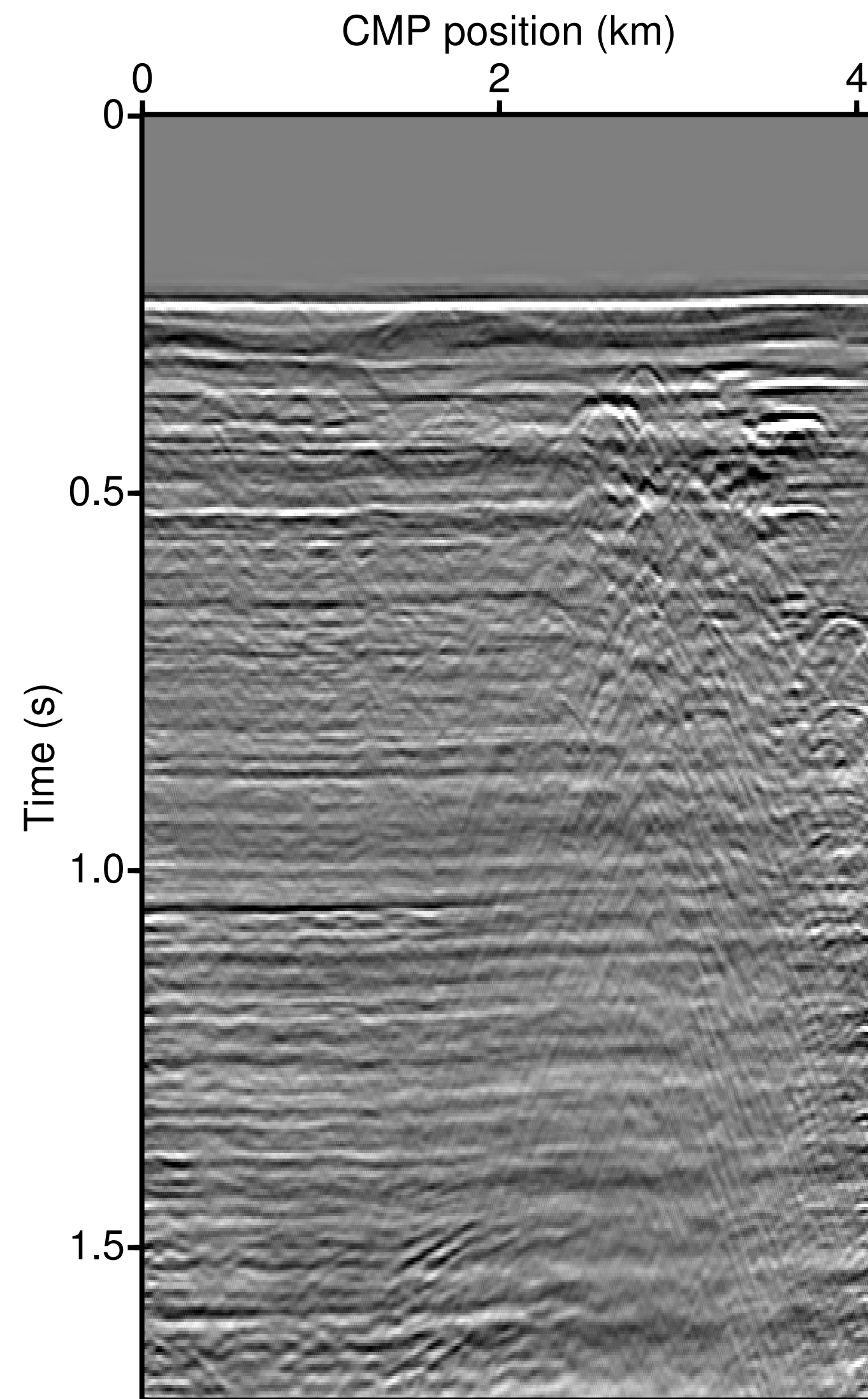


Multiple

**NMO stack**  
**Parabolic Radon Interp**

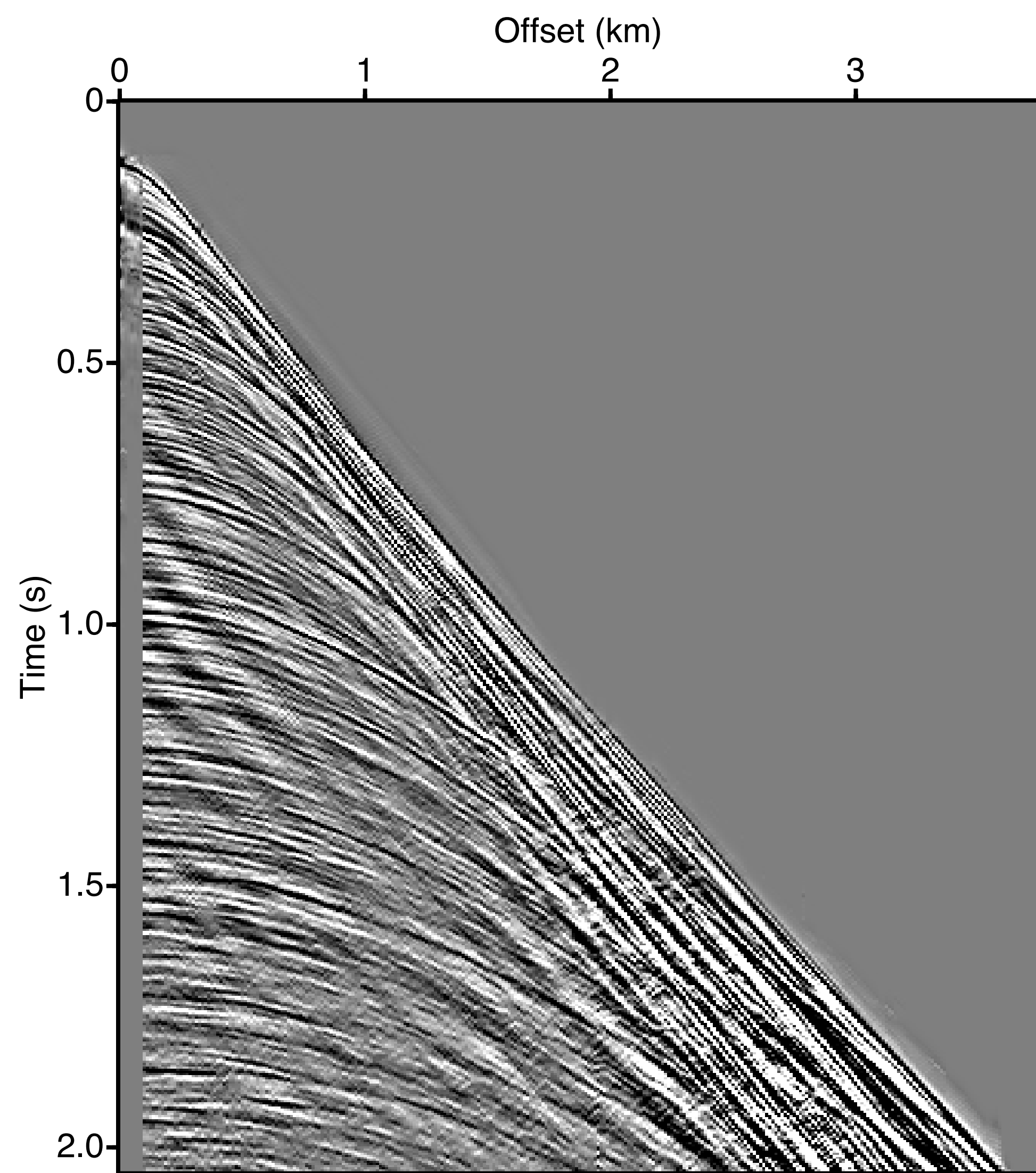


Conservative primary

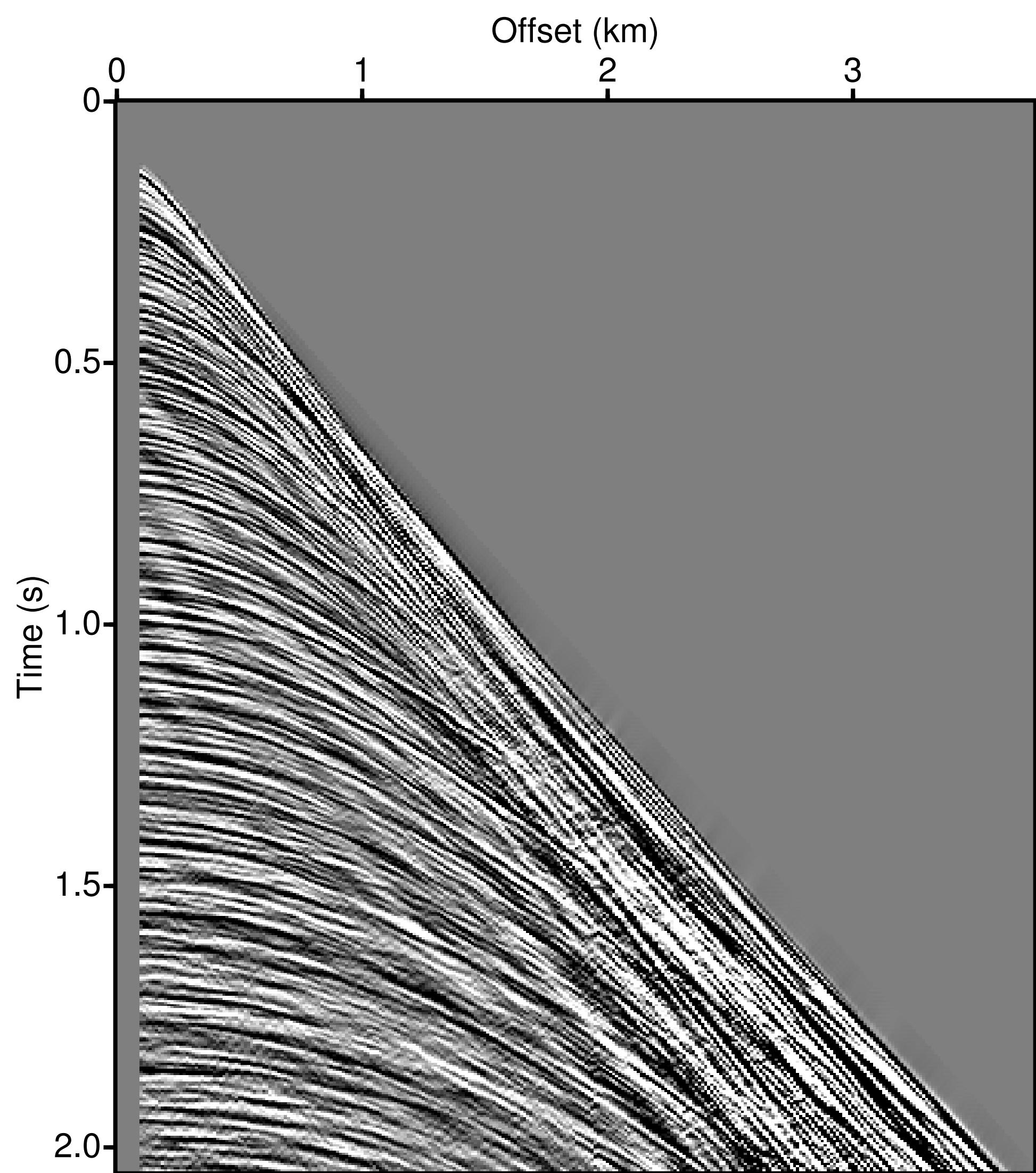


Multiple

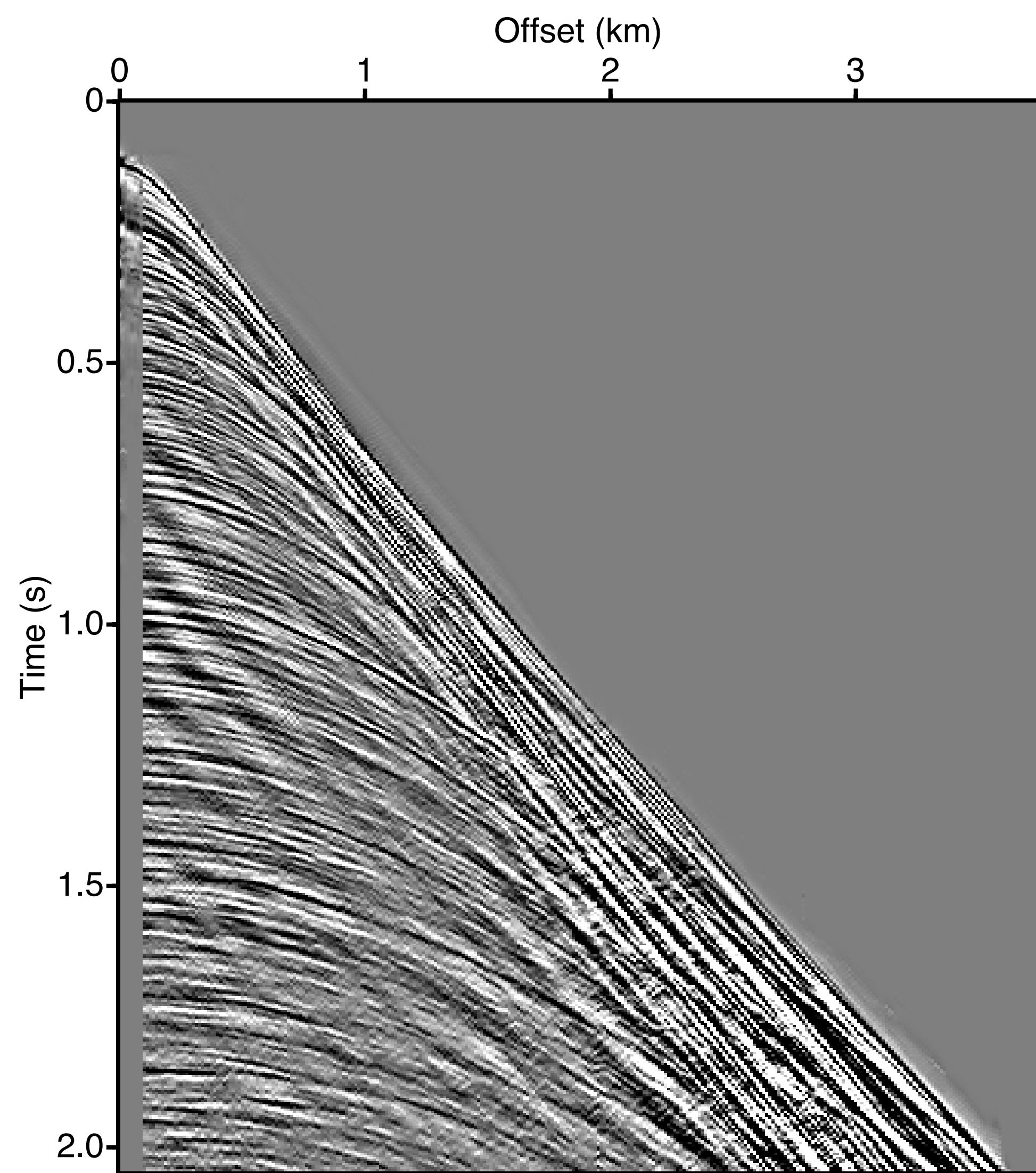
**NMO stack**  
**Re-linearization**  
**Using 3rd Order terms**



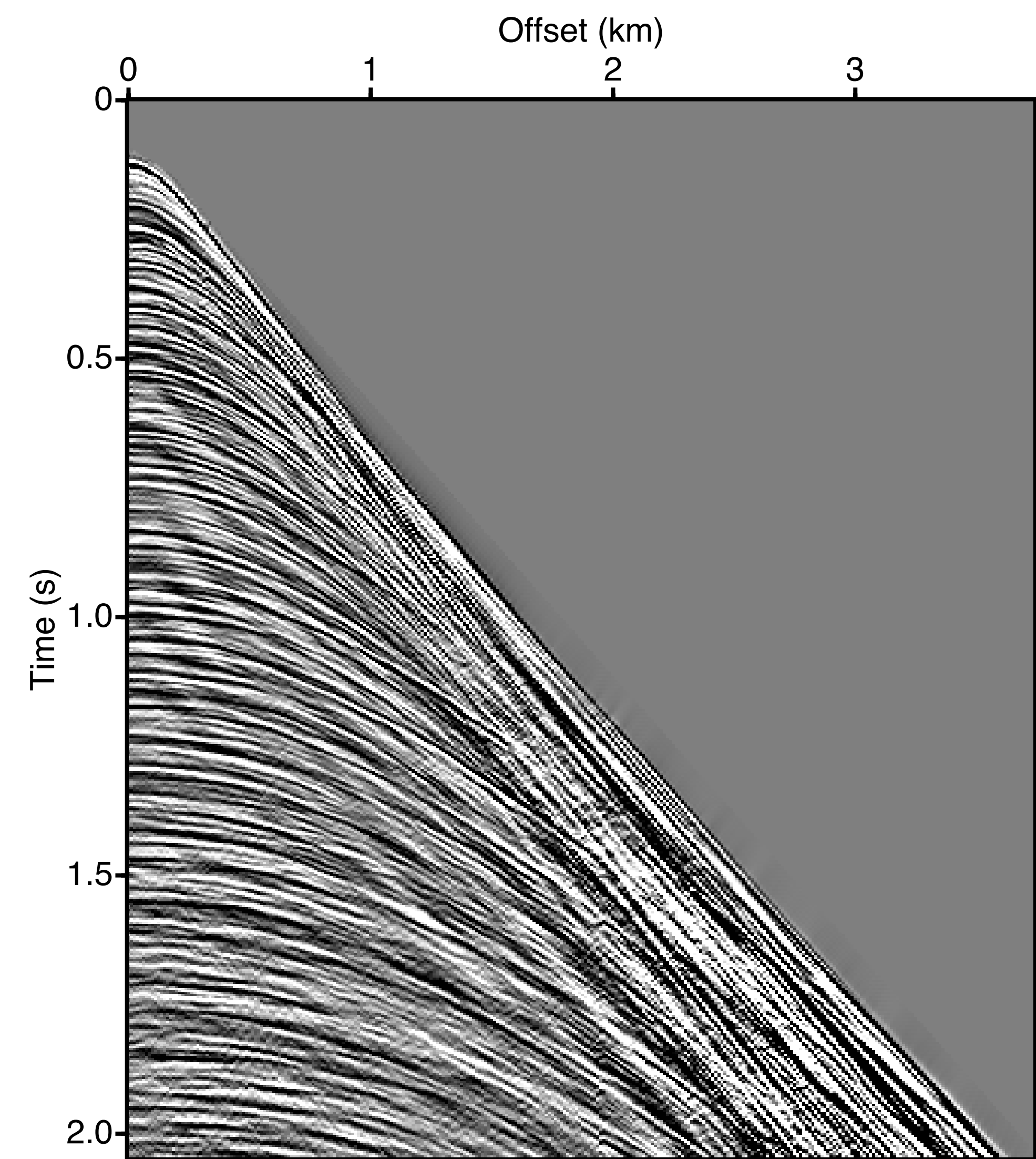
**Direct primary**



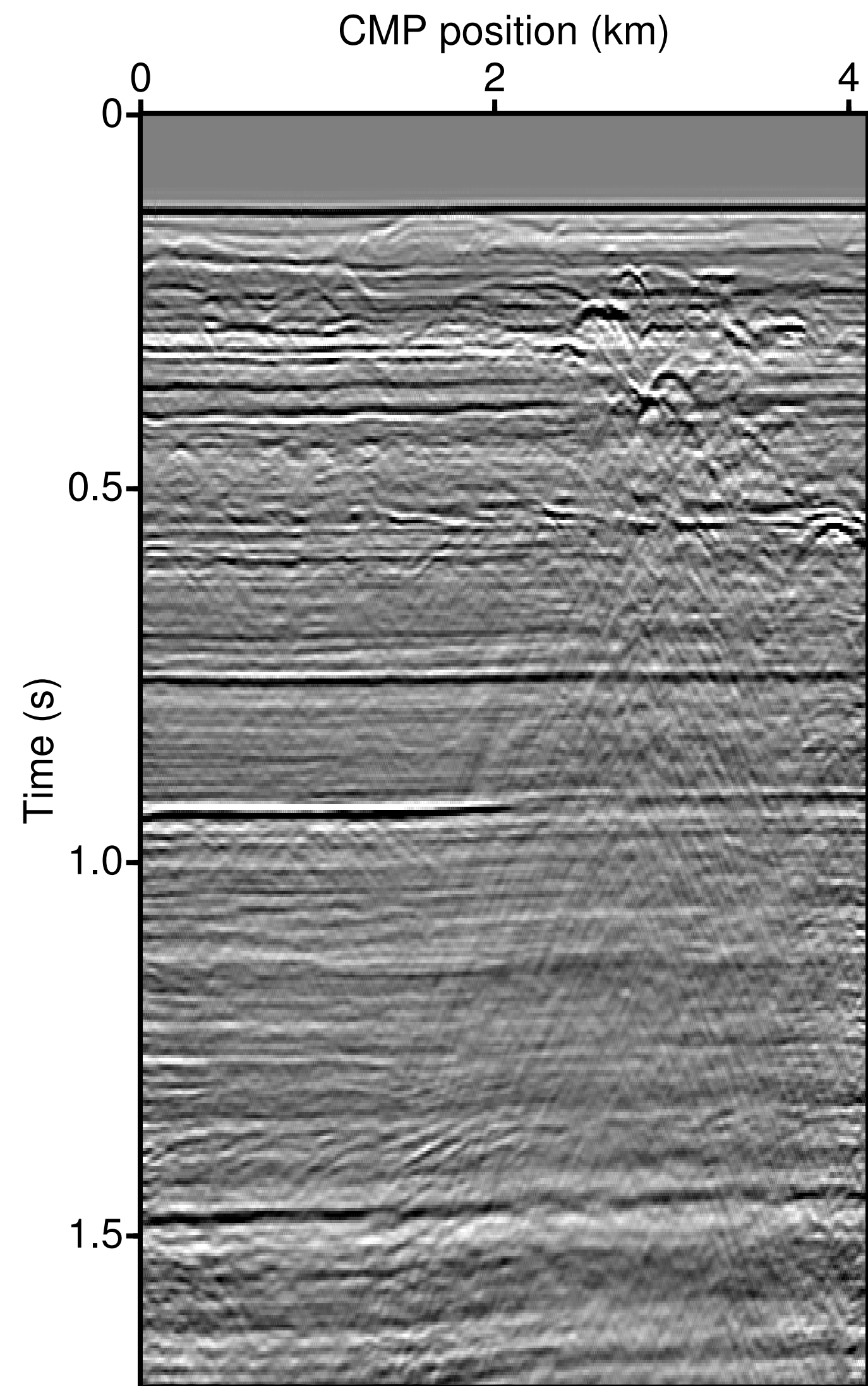
**Original shots**



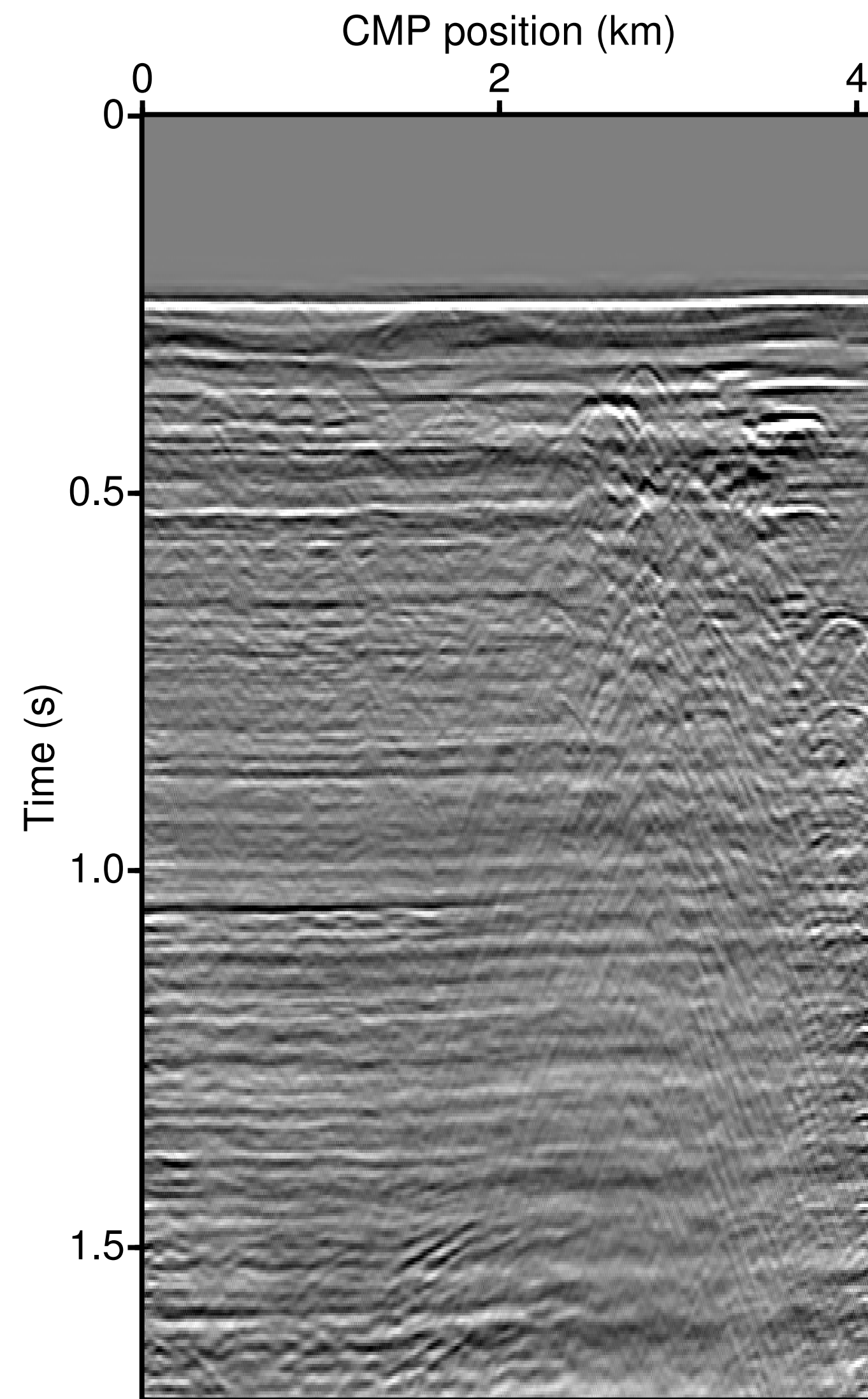
Direct primary shot



Interpolated shot

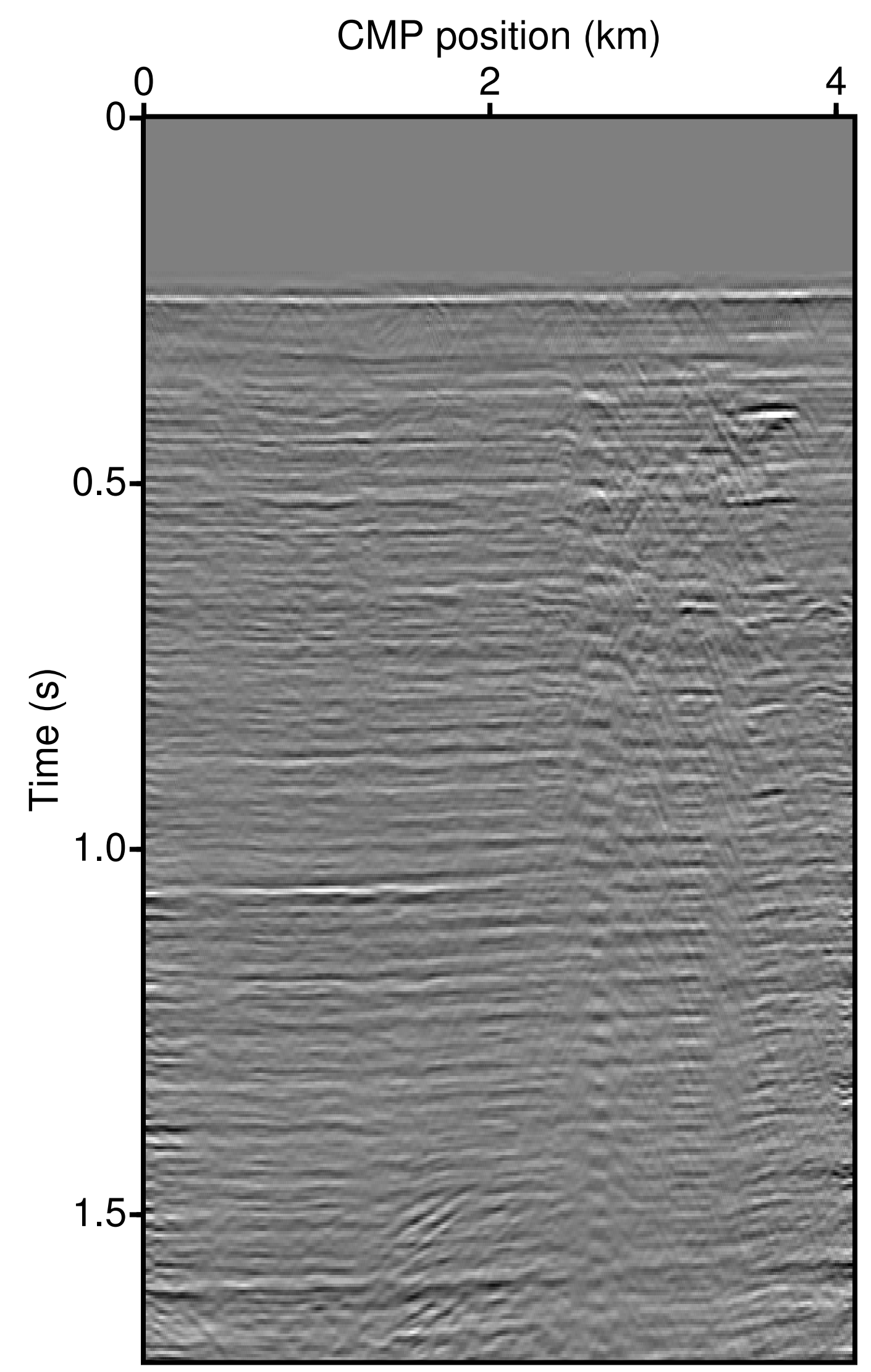


Conservative primary

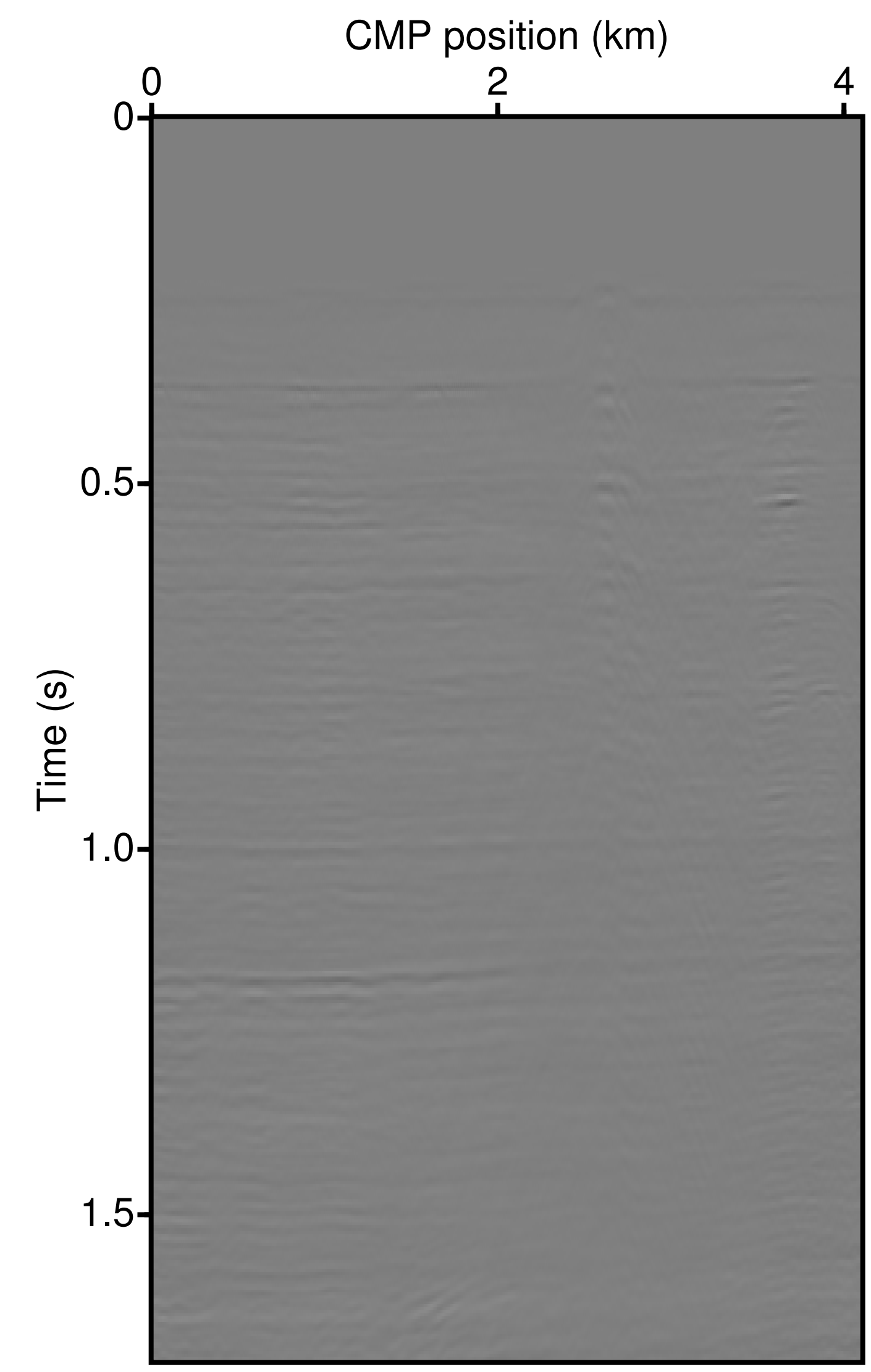


Multiple

**NMO stack**  
**Re-linearization**  
**Using 2nd Order terms**

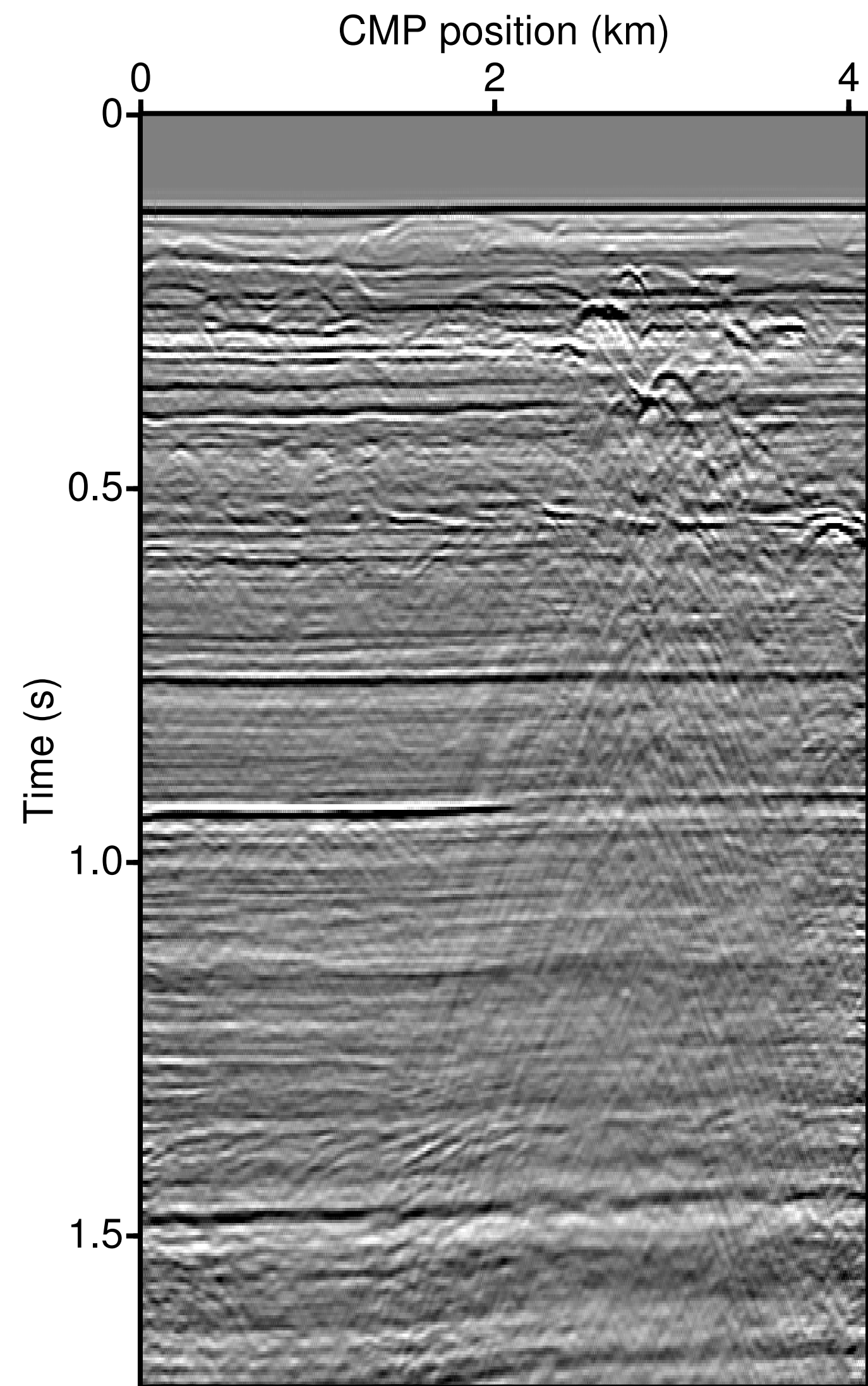


Radon interp - Re-linearization 2nd order

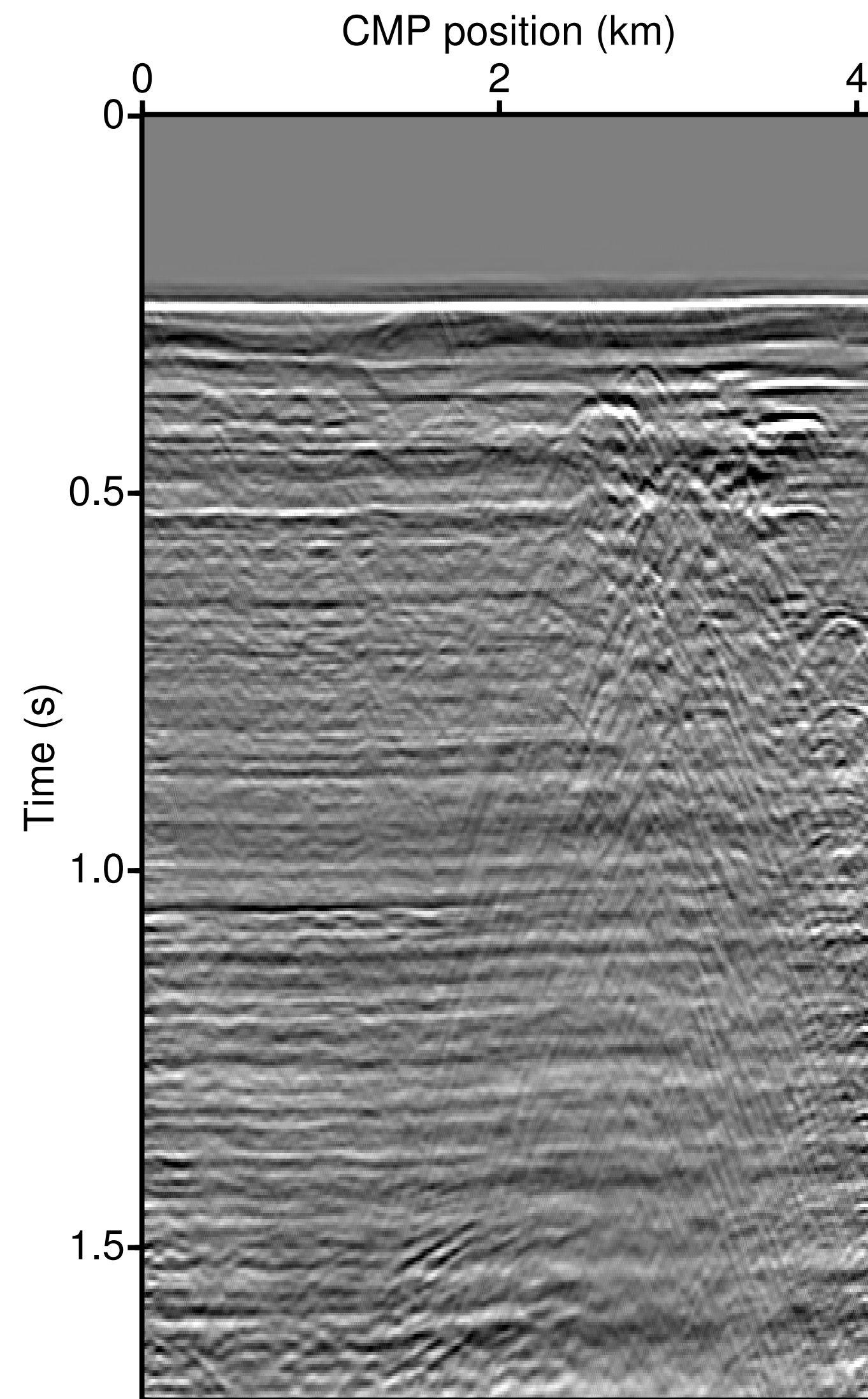


Re-linearization 3rd - 2nd order

**NMO stack**  
**Difference plots**



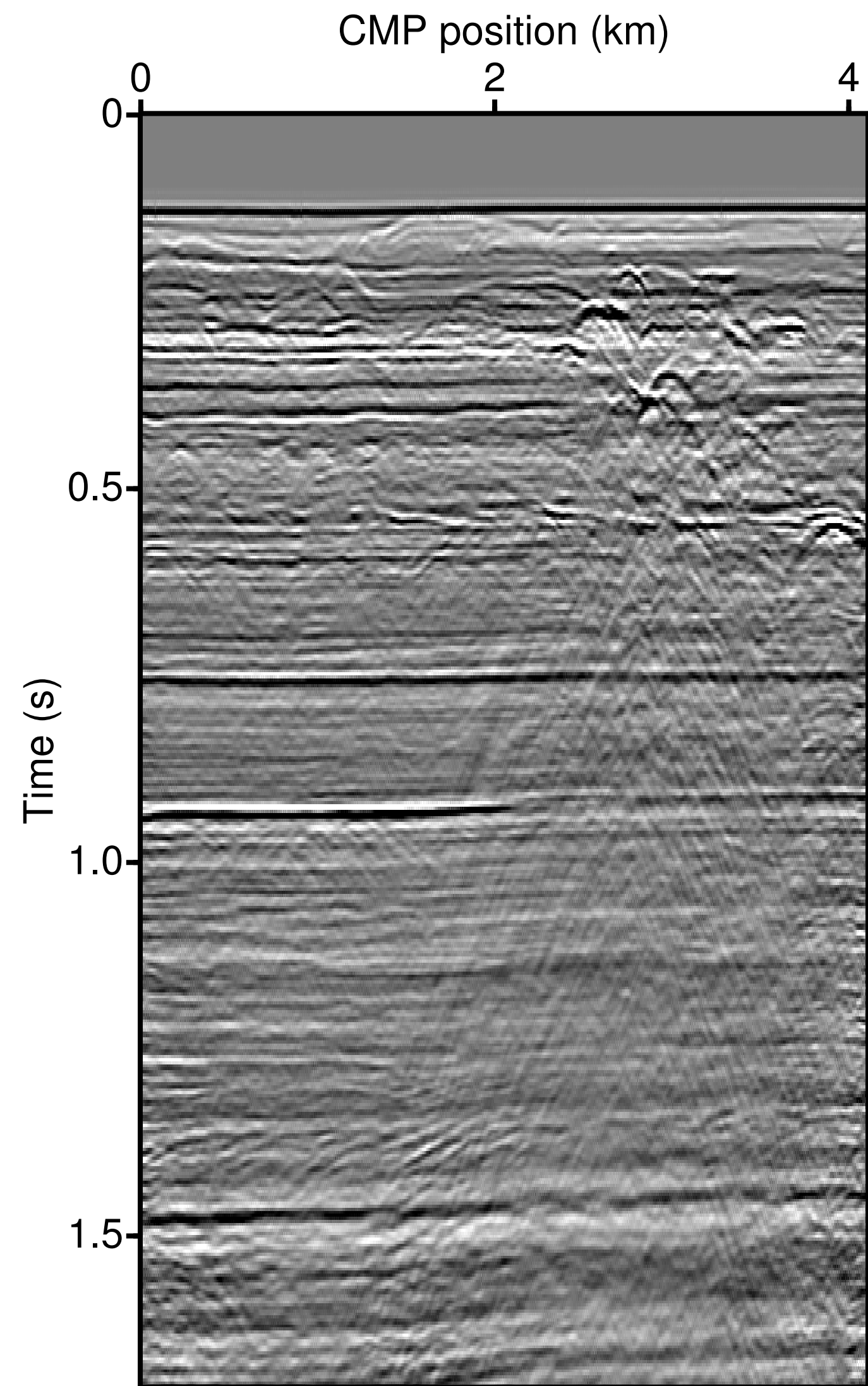
**Conservative primary**



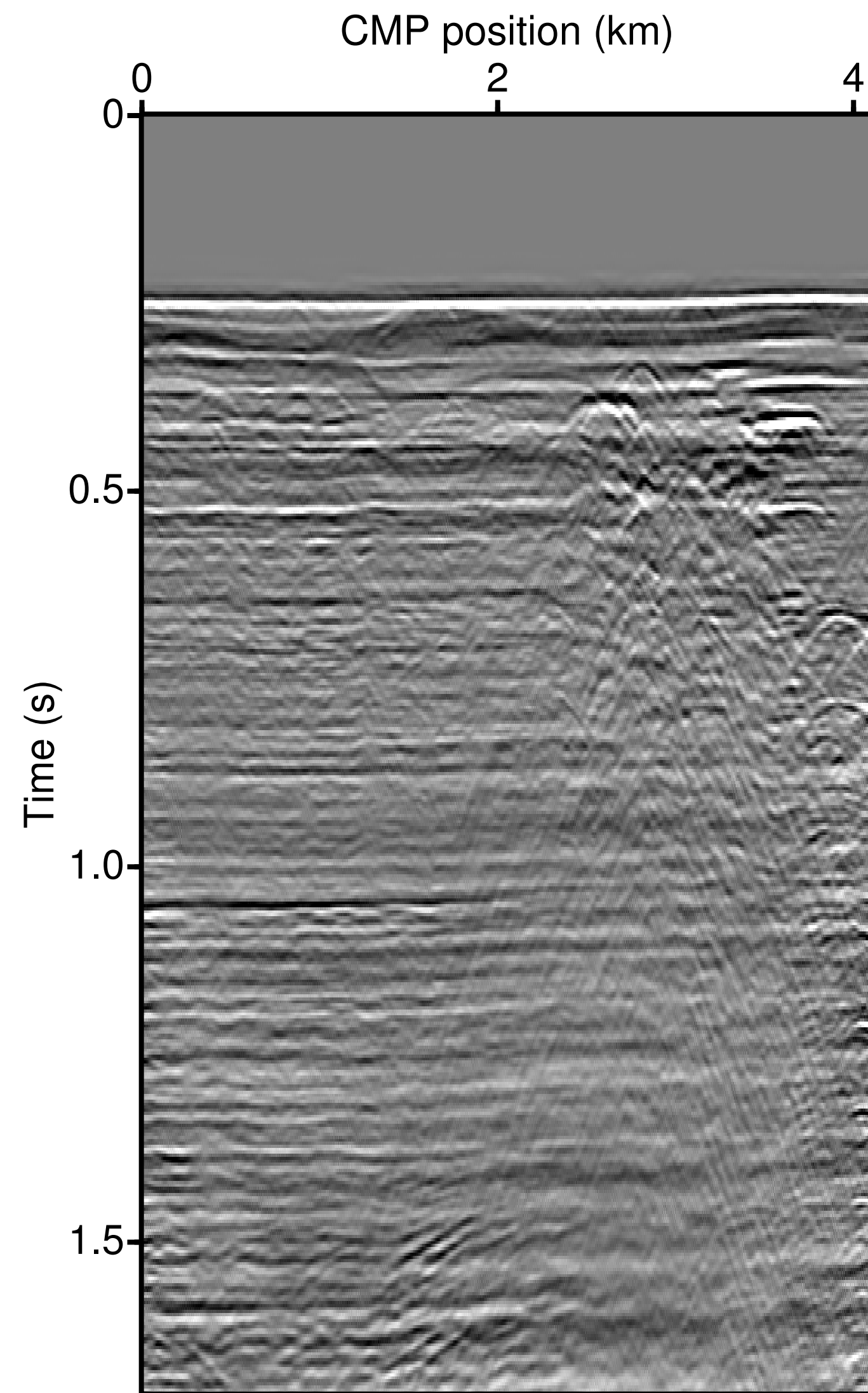
**Multiple**

**NMO stack**  
**Modified Gauss-Newton**  
**Using 3rd Order terms**



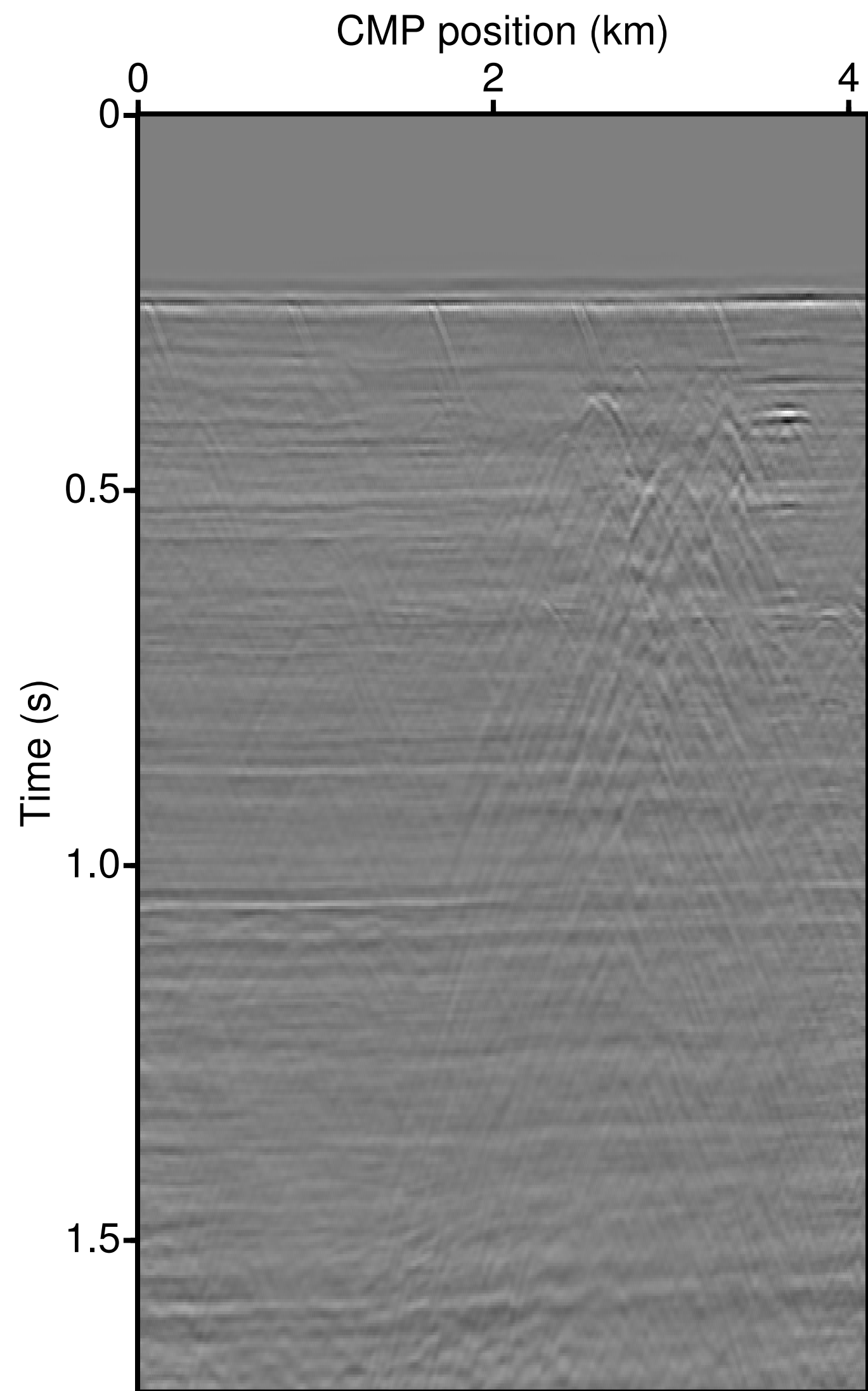


Conservative primary

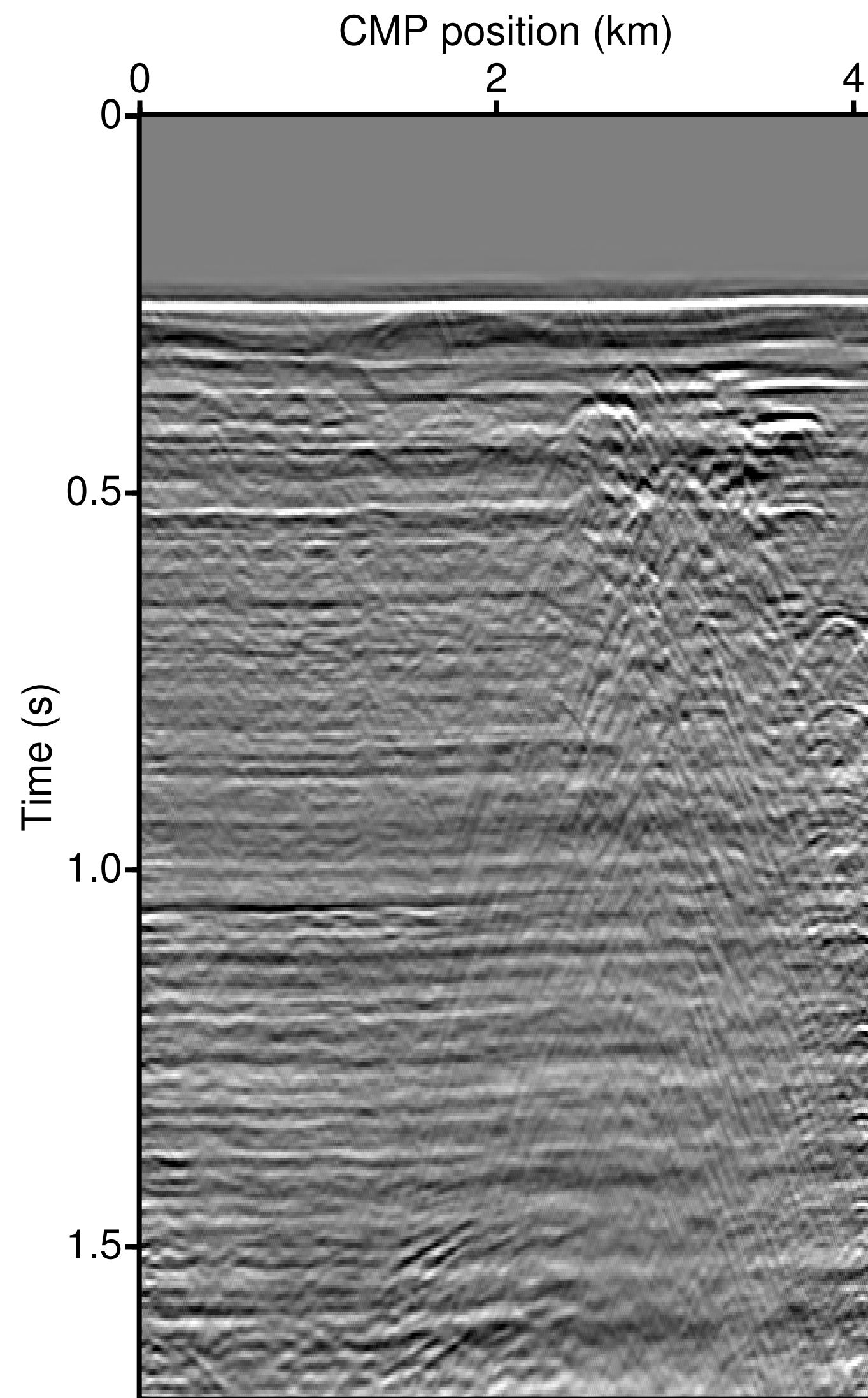


Multiple

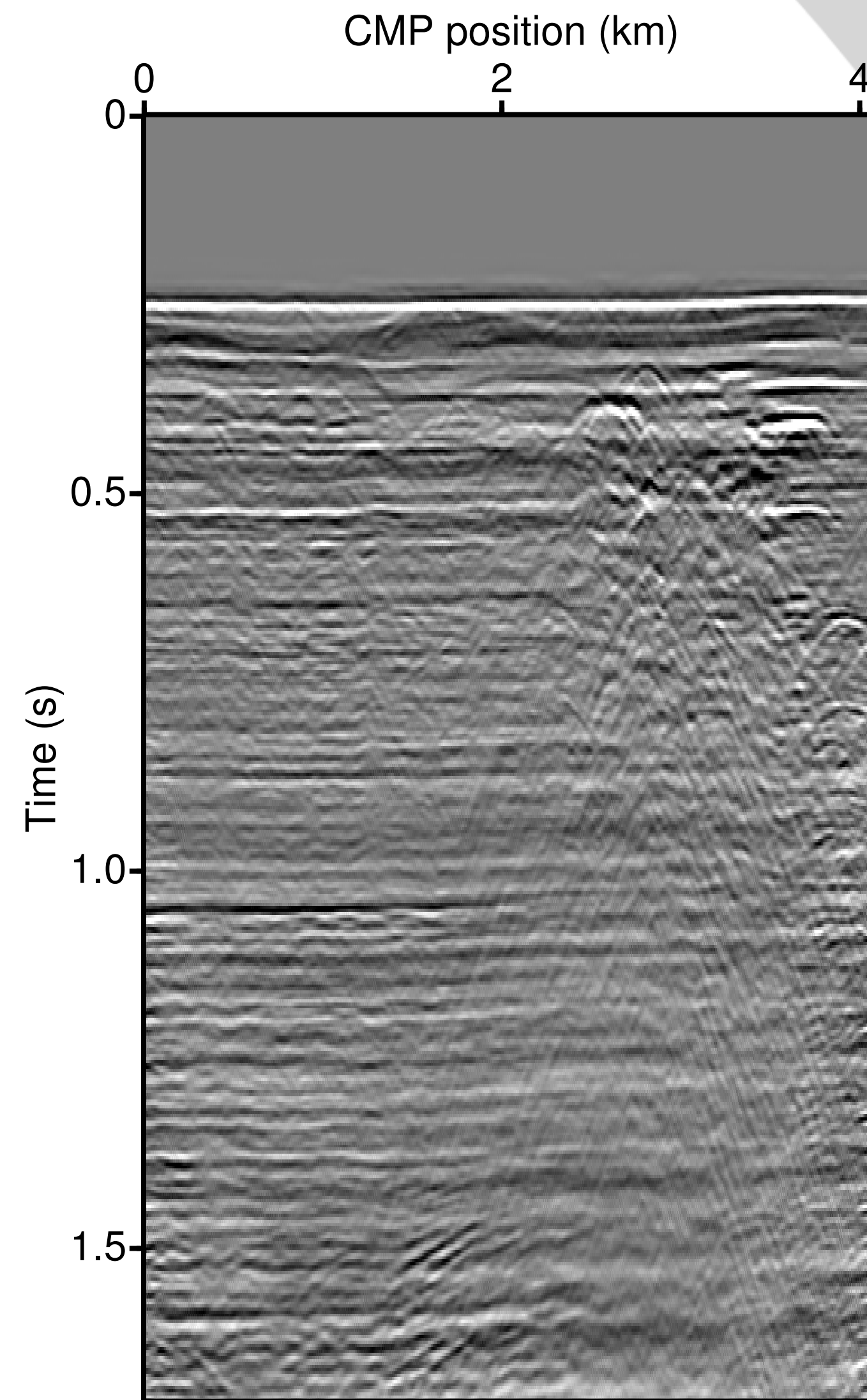
**NMO stack**  
**Re-linearization**  
**Using 3rd Order terms**



**Difference**



**GN 3rd Order Multiple**



**Re-lin. 3rd Order Multiple**

## Discussion and summary

Able to obtain an approximate forward operator with incomplete data without dependence on the missing traces

Inversion should be more stable by not changing the data at each iteration

Further work:

- More careful study needed in comparison to explicit data inversion
- More detailed comparison of algorithms
- What does the infilled  $G$  have to look like? Is it always the “physical” Green’s function?

# Acknowledgements

## PGS for field dataset



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