

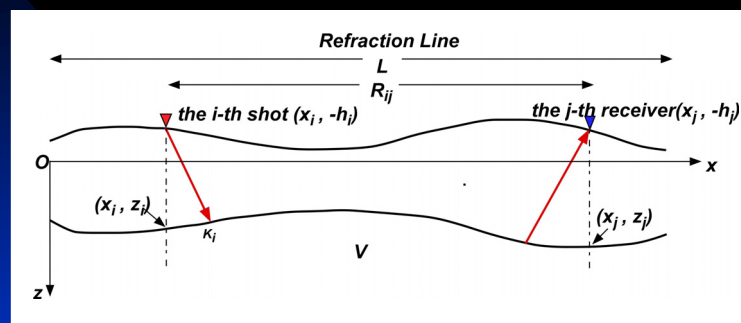
## 2.4 Travel-time inversion

- Time-term method
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## Basic equation

$$t_{ij} = a_i + b_j + R_{ij} / V.$$

$a_i, b_j$  : time-terms defined by

$$a_i = \sqrt{v_{1i}^{-2} - V^{-2}} H_{1i} \quad (i = 1, \dots, m_s),$$

$$b_j = \sqrt{v_{1j}^{-2} - V^{-2}} H_{1j} \quad (j = 1, \dots, m_r).$$

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## Inversion scheme

$$\mathbf{t} = \mathbf{A}\mathbf{m},$$

where

$$\mathbf{t}^T = (t_{11}, t_{12}, \dots, t_{m_s, m_r}),$$

$$\mathbf{m}^T = (a_1, a_2, \dots, a_{m_s}; b_1, b_2, \dots, b_{m_r}; V^{-1}).$$

with

$$A_{pq} = \left. \begin{array}{l} 1 \quad (q = i_p \text{ or } q = m_s + j_p), \\ R_{i_p, j_p} \quad (q = m_s + m_r + 1), \\ 0 \quad \text{otherwise.} \end{array} \right\}.$$

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### Prior constraints between time-terms

$$a_{i_p} - b_{j_p} = \beta_p \quad (p = 1, \dots, n_c).$$

$$\rightarrow \mathbf{c} = \mathbf{Bm}$$

$$\text{with } \mathbf{c}^T = (\beta_1, \beta_2, \dots, \beta_{n_c}),$$

$$B_{pq} = \begin{cases} 1 & (1 \leq p \leq n_c, q = i_p), \\ -1 & (1 \leq p \leq n_c, q = m_s + j_p), \\ 0 & (\text{otherwise}) \end{cases}$$

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$$\begin{bmatrix} \mathbf{t} \\ \mathbf{c} \end{bmatrix} = \begin{bmatrix} \mathbf{A} \\ \mathbf{B} \end{bmatrix} \mathbf{m}.$$

Taking

$$\mathbf{d} = \begin{bmatrix} \mathbf{t} \\ \mathbf{c} \end{bmatrix}, \quad \mathbf{C} = \begin{bmatrix} \mathbf{A} \\ \mathbf{B} \end{bmatrix},$$

$$\mathbf{d} = \mathbf{Cm}$$

Least squares solution

$$\mathbf{C}^T \mathbf{d} = \mathbf{C}^T \mathbf{Cm} \rightarrow \mathbf{m} = (\mathbf{C}^T \mathbf{C})^{-1} \mathbf{C}^T \mathbf{d}.$$

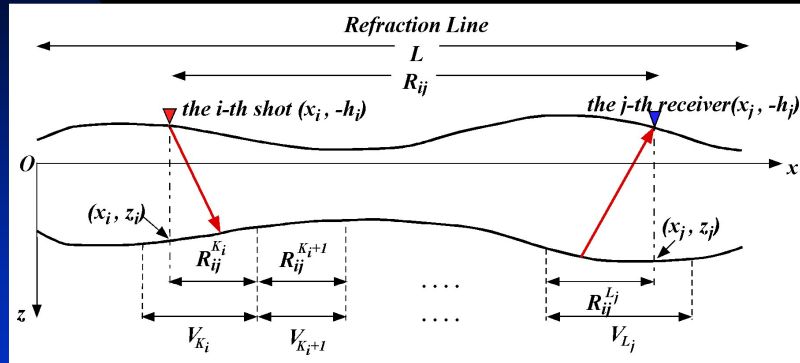
Damped least squares solution

$$\mathbf{m} = (\mathbf{C}^T \mathbf{C} + \alpha \mathbf{I})^{-1} \mathbf{C}^T \mathbf{d}.$$

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### Basic equation

$$t_{ij} = a_i + b_j + \sum_{k=K_i}^{L_j} R_{ij}^k / V_k.$$

$$x = x_1, z = x_3.$$

$a_i, b_j$  : time-terms defined by

$$a_i = \int_{-h_i}^{z_i} \sqrt{v^{-2}(x_i, z) - U_i^2} dz \quad (i = 1, \dots, m_s),$$

$$b_j = \int_{-h'_j}^{z'_j} \sqrt{v^{-2}(x'_j, z) - U_j'^2} dz \quad (j = 1, \dots, m_r).$$

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### Inversion scheme

$$\mathbf{t} = \mathbf{A}\mathbf{m} + \mathbf{e},$$

where

$$\mathbf{t}^T = (t_{11}, t_{12}, \dots, t_{m_s, m_r}),$$

$$\mathbf{m}^T = (a_1, a_2, \dots, a_{m_s}; b_1, b_2, \dots, b_{m_r}; V_1^{-1}, V_2^{-1}, \dots, V_{m_v}^{-1}).$$

and

$$\mathbf{e} \sim N(\mathbf{0}, \sigma^2 \mathbf{E}).$$

### Stochastic model for $\mathbf{m}$ and $\mathbf{t}$

$$p(\mathbf{t} | \mathbf{m}; \sigma^2) = (2\pi\sigma^2)^{-n/2} |\mathbf{E}|^{-1/2} \\ \times \exp\left[-\frac{1}{2\sigma^2} (\mathbf{t} - \mathbf{A}\mathbf{m})^T \mathbf{E}^{-1} (\mathbf{t} - \mathbf{A}\mathbf{m})\right].$$

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Prior constraints :  $a_{i_p} - b_{j_p} = \beta_p$  ( $p = 1, \dots, n_c$ ).

Initial guess :  $\mathbf{m} = \mathbf{m}_0$ .

$$\rightarrow \mathbf{c}_1 = \mathbf{B}_1 \mathbf{m} + \mathbf{d}_1,$$

with  $\mathbf{c}_1^T = (\beta_1, \beta_2, \dots, \beta_{n_c}; m_{o1}, m_{o2}, \dots, m_{om})$ ,

and  $\mathbf{d}_1 \sim N(\mathbf{0}, \rho_1^2 \mathbf{D}_1)$ .

$$p(\mathbf{m}; \rho_1^2) = (2\pi\rho_1^2)^{-r_1/2} |\mathbf{D}_1|^{-1/2} \exp\left[-\frac{1}{2\rho_1^2} (\mathbf{c}_1 - \mathbf{B}_1 \mathbf{m})^T \mathbf{D}_1^{-1} (\mathbf{c}_1 - \mathbf{B}_1 \mathbf{m})\right].$$

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### Smoothness constraint

$$b_{j-1} - 2b_j + b_{j+1} = 0 \quad (j = 2, \dots, m_r - 1).$$

$$\rightarrow \mathbf{0} = \mathbf{B}_2 \mathbf{m} + \mathbf{d}_2,$$

$$\text{with } \mathbf{d}_2 \sim N(\mathbf{0}, \rho_2^2 \mathbf{D}_2).$$

$$p(\mathbf{m}; \rho_2^2) = (2\pi\rho_2^2)^{-r_2/2} |\mathbf{D}_2|^{-1/2} \exp\left[-\frac{1}{2\rho_2^2} (\mathbf{B}_2 \mathbf{m})^T \mathbf{D}_2^{-1} (\mathbf{B}_2 \mathbf{m})\right].$$

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### Likelihood function

$$l(\mathbf{m}; \sigma^2, \rho_1^2, \rho_2^2 | \mathbf{d}) = p(t | \mathbf{m}; \sigma^2) p(\mathbf{m}; \rho_1^2) p(\mathbf{m}; \rho_2^2).$$

$$l(\mathbf{m}; \sigma^2, \alpha_1^2, \alpha_2^2 | \mathbf{d}) = (2\pi\sigma^2)^{-(n+r_1+r_2)/2} (\alpha_1^2)^{r_1/2} (\alpha_2^2)^{r_2/2} \\ \times |\mathbf{E}|^{-1/2} |\mathbf{D}_1|^{-1/2} |\mathbf{D}_2|^{-1/2} \exp\left[-\frac{1}{2\sigma^2} s(\mathbf{m})\right],$$

with

$$s(\mathbf{m}) = (\mathbf{t} - \mathbf{A}\mathbf{m})^T \mathbf{E}^{-1} (\mathbf{t} - \mathbf{A}\mathbf{m}) + \alpha_1^2 (\mathbf{c}_1 - \mathbf{B}_1 \mathbf{m})^T \mathbf{D}_1^{-1} (\mathbf{c}_1 - \mathbf{B}_1 \mathbf{m}) \\ + \alpha_2^2 (\mathbf{B}_2 \mathbf{m})^T \mathbf{D}_2^{-1} (\mathbf{B}_2 \mathbf{m}).$$

$$\mathbf{m}^* = (\mathbf{A}^T \mathbf{E}^{-1} \mathbf{A} + \alpha_1^2 \mathbf{B}_1^T \mathbf{D}_1^{-1} \mathbf{B}_1 + \alpha_2^2 \mathbf{B}_2^T \mathbf{D}_2^{-1} \mathbf{B}_2)^{-1} \\ \times (\mathbf{A}^T \mathbf{E}^{-1} \mathbf{t} + \alpha_1^2 \mathbf{B}_1^T \mathbf{D}_1^{-1} \mathbf{c}_1).$$

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$$A_{pq} = \begin{cases} 1 & (q = i_p \text{ or } q = m_s + j_p), \\ R_{i_p, j_p}^{q - (m_s + m_r)} & (m_s + m_r + K_{i_p} \leq q \leq m_s + m_r + L_{j_p}), \\ 0 & \text{otherwise.} \end{cases}$$

$$B_{1,pq} = \begin{cases} 1 & (1 \leq p \leq n_c, q = i_p), \\ -1 & (1 \leq p \leq n_c, q = m_s + j_p), \\ 1 & (n_c + 1 \leq p \leq n_c + m), \\ 0 & (\text{otherwise}) \end{cases}$$

$$B_{2,pq} = \begin{cases} 1 & (q = m_s + p), \\ -2 & (q = m_s + p + 1), \\ 1 & (q = m_s + p + 2), \\ 0 & (\text{otherwise}). \end{cases}$$

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$$ABIC = (-2)L(\sigma^2, \alpha_1^2, \alpha_2^2),$$

$$\text{with } L(\sigma^2, \alpha_1^2, \alpha_2^2) = \int l(\mathbf{m}; \sigma^2, \alpha_1^2, \alpha_2^2 | \mathbf{d}) d\mathbf{m}.$$

Minimizing  $ABIC$  requires

$$\partial L(\sigma^2, \alpha_1^2, \alpha_2^2) / \partial \sigma^2 = \partial L(\sigma^2, \alpha_1^2, \alpha_2^2) / \partial \alpha_1^2 = \partial L(\sigma^2, \alpha_1^2, \alpha_2^2) / \partial \alpha_2^2 = 0.$$

$$\rightarrow \sigma^2 = s(\mathbf{m}^*) / (n + r_1 + r_2 - m),$$

and

$$ABIC(\alpha_1^2, \alpha_2^2) = (n + r_1 + r_2 - m) \log s(\mathbf{m}^*) - r_1 \log(\alpha_1^2) - r_2 \log(\alpha_2^2) \\ + \log | \mathbf{A}^T \mathbf{E}^{-1} \mathbf{A} + \alpha_1^2 \mathbf{B}_1^T \mathbf{D}_1^{-1} \mathbf{B}_1 + \alpha_2^2 \mathbf{B}_2^T \mathbf{D}_2^{-1} \mathbf{B}_2 | + C.$$

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## Final solution

$$\hat{\mathbf{m}} = (\mathbf{A}^T \mathbf{E}^{-1} \mathbf{A} + \hat{\alpha}_1^2 \mathbf{B}_1^T \mathbf{D}_1^{-1} \mathbf{B}_1 + \hat{\alpha}_2^2 \mathbf{B}_2^T \mathbf{D}_2^{-1} \mathbf{B}_2)^{-1} \\ \times (\mathbf{A}^T \mathbf{E}^{-1} \mathbf{t} + \hat{\alpha}_1^2 \mathbf{B}_1^T \mathbf{D}_1^{-1} \mathbf{c}_1),$$

and

$$\hat{\sigma}^2 = s(\hat{\mathbf{m}}) / (n + r_1 + r_2 - m).$$