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12.510 Introduction to Seismology
Spring 2008

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✧ Go back to the observations again and look at the deviation from the model.

Objective: we need to find a model that minimize δt

$$T_{obs} = \underbrace{3D \text{ structure} + \text{error in source location} + \text{noise (instrument, measurement)}}_{\text{Hypocenter: } t_0, x, y, z \text{ (or } \theta, \phi, r)}$$

$$\Rightarrow \delta t = \delta t_{3D} + \delta t_{\text{mislocation}} + \delta t_{\text{noise}}$$

Errors caused by the model and the source location are usually combined together, and the noise is assumed to be white, with a Gaussian distribution.

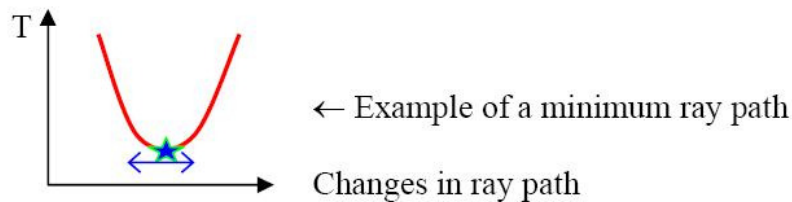
If we know the 1D model, we can apply **Snell's law** to estimate the geometry:

$$T_{obs} = \int_{\substack{3D \\ \text{Ray} \\ \text{Path}}} \frac{1}{c(x)} dl$$

Note that

$$\nabla T(x) = \frac{1}{c(x)} k$$

If c change, the ray path changes. We end up with a nonlinear problem. Thus, we should try to linearize the inversion, using **the Fermat's Principle**.



If we change a little bit the ray path around the optimum, we'll end up with a small change in travel time. We have two kinds of “deviations” from the reference ray:

1. First contribution: effect of changes in velocity Δc .
2. Second contribution: effect of change in the ray path. Fermat's principle says that we can ignore it.

Linearization of the travel time

Travel time residual:

$$\begin{aligned}
 \text{Observation} = \delta t_{3D} = T_{obs} - T_{ref} &= \int_{\substack{\text{true} \\ 3D \\ \text{structure}}} \frac{1}{c(\underline{x})} dl - \int_{\substack{\text{reference} \\ 3D \\ \text{path}}} \frac{1}{c_0(\underline{x})} dl_0 \\
 &\stackrel{\text{Fermat's Principle}}{\approx} \int_{\substack{\text{reference} \\ 3D \\ \text{path}}} \frac{1}{c(\underline{x})} dl_0 - \int_{\substack{\text{reference} \\ 3D \\ \text{path}}} \frac{1}{c_0(\underline{x})} dl_0 \\
 &= \int_{\substack{\text{reference} \\ 3D \\ \text{path}}} \frac{\Delta c}{c_0^2} dl_0 = \int_{\substack{\text{reference} \\ 3D \\ \text{path}}} (s(\underline{x}) - s_0(\underline{x})) dl_0 \\
 &= \int_{\substack{\text{reference} \\ 3D \\ \text{path}}} (\Delta s(\underline{x})) dl_0
 \end{aligned}$$

In linearizing the problem, we get rid of the unknown ray. We can do our calculation in a reference earth model.

- ✧ The travel time tomography is an iterative process:
- ✧ Create 1D model
- ✧ Ray tracing and get new rays in the model
- ✧ Update ray geometry
- ✧ Get the reference ray related to the 3D

$$\delta t = T_{obs} - T_{ref} (3D)$$

(The reference model does not have to be a 1D model.)

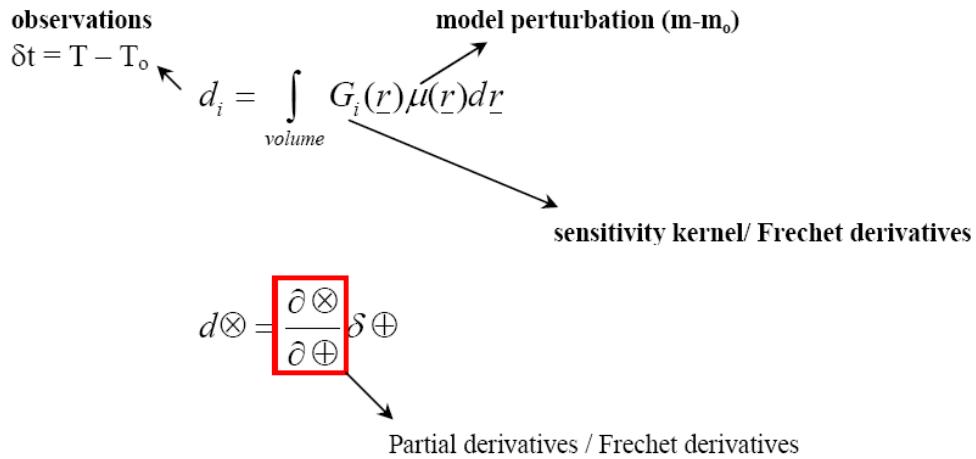
Linearization of the hypocenter mislocation

$$\begin{aligned}
 \delta t_{misloc} &= \frac{\partial T}{\partial t_o} \delta t_o + \frac{\partial T}{\partial x} \delta x + \frac{\partial T}{\partial y} \delta y + \frac{\partial T}{\partial z} \delta z \\
 \delta \otimes &= \frac{\partial \otimes}{\partial \oplus} \delta \oplus
 \end{aligned}$$

with t_o the origin time, (x, y, z) the location of the earthquake.

Then we try to solve for Δs , δt , δx , δy , δz .

Inverse Problem



First, we need to discretize the problem, i.e. **parameterization**:

$$\mu(\underline{r}) = \sum_{k=1}^M \gamma_k h_k(\underline{r})$$

γ_k : weight
 h_k : basis function

For example, plane wave summation:

$$\phi = \iiint \Phi(x, y, z, \omega) e^{i(\underline{k} \cdot \underline{x} - \omega t)} d\underline{k} d\omega$$

Then, we inject μ into the equation:

$$d_i = \sum_{k=1}^M \underbrace{\left\{ \int G_i(\underline{r}) h_k(\underline{r}) d\underline{r} \right\}}_{\text{kernel projected on the basis function h}} \gamma_k$$

kernel projected on the basis function h

$$d_i = \sum_{k=1}^M A_{ik} \gamma_k \text{ for } i=1, 2, \dots, N \text{ data}$$

sensitivity matrix
 kernel projected on the basis functions

projector

$$\underline{d} = \underline{A} \underline{m}$$

data

model (includes the values of the weight)

$$m = (\gamma_1, \gamma_2, \dots, \gamma_M)$$

where

G_i : **Green functions**, solution of a point source. We need to do a convolution with a point perturbation in order to get the observations.

M : Number of model parameters.

N : Number of observations.

In general, $M \neq N$. As a consequence, the matrix \underline{A} is not square.

$$A = \left(\begin{array}{c} \\ \\ \\ \end{array} \right) \begin{array}{l} \updownarrow \\ \text{N rows} \end{array}$$

$$\begin{array}{c} \leftarrow \rightarrow \\ \text{M columns} \end{array}$$

Multiplying the equation by A^T , we can get the solution:

$$\rightarrow \hat{m} = (A^T A)^{-1} A^T \underline{d} \quad \text{Generalized Least Squares inversion}$$

$$\| \hat{m} - (A^T A)^{-1} A^T \underline{d} \| = \varepsilon \rightarrow \text{Goal is to minimize } \varepsilon.$$

Back to our specific inverse problem:

$$\delta t = \int \Delta s \cdot dl \rightarrow \text{parametrize } \Delta s$$

$$\Delta s = \sum_{k=1}^M \gamma_k h_k$$

One way is to take h_k as a series of cells/blocks, with a value for \underline{x} inside the cell k and zero otherwise. We have

$$\delta t_i = \int \Delta s dl = \sum_{k=1}^{M \text{ cell}} \Delta s_k (dl)_{ik}$$

where

i : event-station pair.

$(dl)_{ik}$: path length.

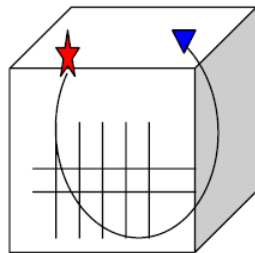
Rewrite the equation in the matrix form:

$$A_{ik} \cdot m = \begin{bmatrix} \Delta l_{11} & \dots & \Delta l_{1M} \\ \vdots & \vdots & \vdots \\ \Delta l_{N1} & \dots & \Delta l_{NM} \end{bmatrix} \begin{bmatrix} \Delta s_1 \\ \vdots \\ \Delta s_M \end{bmatrix} = \begin{bmatrix} \delta t_1 \\ \vdots \\ \delta t_N \end{bmatrix}$$

where each ray gives a row in the matrix.

We have an average wavespeed along the ray. In order to construct a model vector, we need to get data from different rays crossing each other.

A is a sparse matrix. If we look at one ray:



$M \sim 300,000$
 ~ 20 layers
 the ray samples ~ 100 cells

A will have only ~ 100 elements non-zero. The good thing about sparse matrix is that $A^T A$ is approximately diagonal. The problem is that there are many singularities, which make the inversion unstable (in that case, we need to add a damping factor or regularize the problem). One possibility is to not use cells of the same size. Consequently, it reduces the number of cells; the inverse matrix is less singular. Nevertheless, the computation time increases.

Another way is take h_k as spherical harmonics (in global seismology).