Multiple Event Location at ISC?

Keith McLaughlin IASPEI General Assembly Santiago Chile 2005

Motivation - I

- The purpose of this workshop is to propose and discuss procedures that would improve routine daily ISC locations.
- The purpose of this paper is to generate discussion!

Motivation - II

- WHY MULTIPLE EVENT LOCATION (MEL)?
- Path effects dominate location bias. Path effects are persistent for multiple adjacent events to common stations.
- Master event, JHD, HDC, and Double-Difference methods have demonstrated that relative locations between events in clusters are more accurate than individual event locations. The absolute locations of poorly located events are improved relative to the better located events
- With the exception of local data & depth phases, adding secondary phases does not promise the same potential for location improvement as MEL

Attempted Demonstration with NTS GT Data

- Large number of GT0 events provide demonstration with known answer
- Choose a subset of events for demonstration purposes
- Can we better detect outliers in MEL?

Methodology

- 1. Single Event Locations (SEL)
- 2. Multiple Event Locations (MEL)
 - Heavily regularized inversion based on correlated model and data variance weighting
- 3. Identify event residual patterns (ERPs) that do not look like other events

Multiple Event Location (MEL)

 $T^{obs}(i,j) = T^{pred}(\underline{R}(i),\underline{R}(j)) + c(\underline{R}(i))$ for i'th station and j'th event

Starting with Single Event Location (SEL), m = [x(1,...,Ne), y(1,...,Ne)]Incrementally solve, **A** m' = d

Model vector, m' = $[\delta x(1,...,Ne), \delta y(1,...,Ne), c(1,...,Nsta)]'$

Data vector, d = [Tobs(1,...,Ndata)-Tpred(1,...,Ndata), constraint(1,...,Ncon)]' Model covariance matrix, C_m , constructed from correlation model

 $<\delta x_j \delta x_k > = \sigma_x^2 e^{-Djk/D0}$ (neighboring events have similar solution) $<\delta y_j \delta y_k > = \sigma_y^2 e^{-Djk/D0}$

 $\langle \delta c_p \delta c_q \rangle = \sigma_c^2 e^{-Dpq/C0}$ (neighboring stations have similar path effect) Data covariance matrix, C_d , constructed from prior locations

 $C_d \sim \sigma_o^2$ if residual < less than $2\sigma_o$, otherwise $C_d \sim d^2$ Effectively consistent with "uniform reduction"

Diagonal matrix ignores correlated errors

Solve linear system, (A' $C_d^{-1}A - C_m^{-1}$) m' = $C_d^{-1}d$, using bi-conjugate gradient or sub-space methods

NTS GT0

401 NTS GT0 events

NTS GT0 - 825 teleseismic stations 2600 2400 37.3 Yucea 2200 37.2 2000 1800 37.1 1600 1400 37 1200 km 1000 36.9 10 20 800 -116.5 -116.4' -116.3' -116.2' -116.1' -116 -115.9 -116.6







significant variance reduction more Gaussian with reduced tails Obvious outliers are more obvious!





Tails (outliers) tend to be located at same stations and networks

Is the residual pattern similar?



- Common stations for events J & K
- Test some simple metrics?

Residual Pattern Anomaly Detection?

For common stations at pairs of events, j & k examine some test statistics for events that do not match

Residual difference between residual patterns $D_{jk} = \Sigma_t (R_{ij} - R_{ik})^2 / \sigma_j \sigma_k$

Robust difference between residual patterns

 $D'_{jk} = Median_{\iota} |R_{ij} - R_{ik}| / Median_{\iota} |R_{ij}| / Median_{\iota} |R_{ik}|$

Correlation between residual patterns,

$$\rho_{jk} = \Sigma_{\iota} \left(R_{ij*} R_{ik} \right) / \left| R_{ij} \right| \left| R_{ik} \right|$$

Flagged SEL Residual Patterns (differences)



Flagged MEL Residual Patterns (1-correlation)





Summary

- MEL is inherently more stable and straight forward than SEL
- Some location outliers are detected based on residual patterns
- Promising but incomplete analysis of an automated outlier detection procedure
 - Need to complete the loop on outlier rejection and comparison with GT locations