BAYESIAN TREATY MONITORING: PRELIMINARY REPORT

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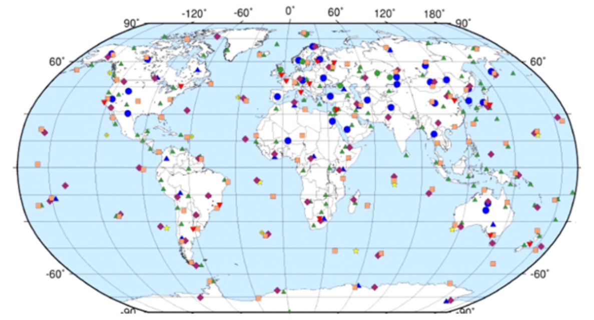
Introduction

• Global seismic monitoring for the **Comprehensive Nuclear-Test-Ban Treaty (CTBT)** aims to recover the time, location, depth, and magnitude for all seismic events in the magnitude range of interest.

• Data from the International Monitoring System (IMS) are processed in real time at the International Data Centre (IDC) in Vienna. Our goal is to improve the sensitivity and accuracy of automated processing at IDC.

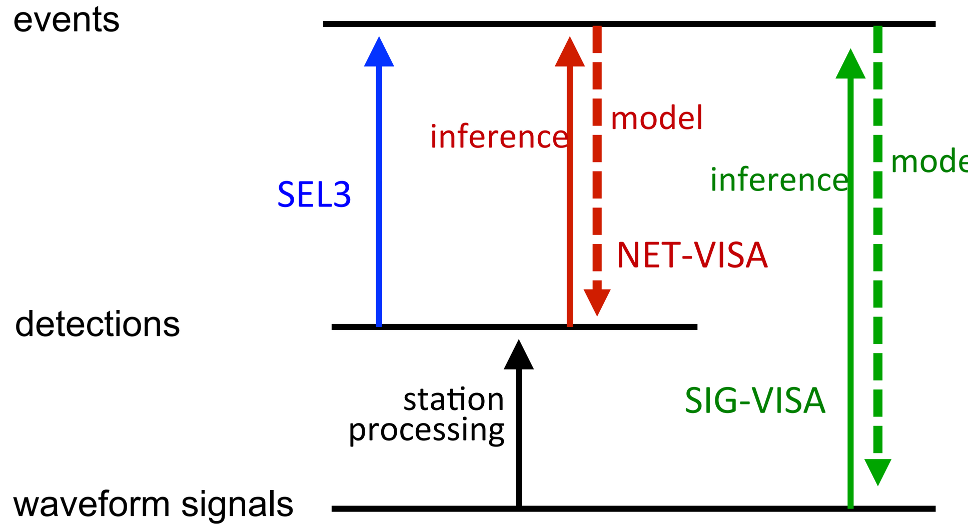


Blue dots and triangles are primary seismic stations.

•NET-VISA is a *detection-based* Bayesian monitoring system whose performance is limited by the classical, bottom-up, threshold-based detections algorithms used in station processing.

• SIG-VISA, a *signal-based* system, will use generative models that span the range from events to waveform traces. It will have several qualitative advantages over NET-VISA, potentially yielding a significant improvement in detection performance

Signal-Based vs. Detection-Based Monitoring



Bayesian monitoring with a generative approach

P_ϕ(world) describes prior probability for what *is* (*events*)

P_ϕ(signal | world) describes forward model (propagation, measurement, etc.)

Detection-based Bayesian monitoring:

P(world | f (signal)) ~ P_ϕ(f (signal) | world) P_ϕ(world)

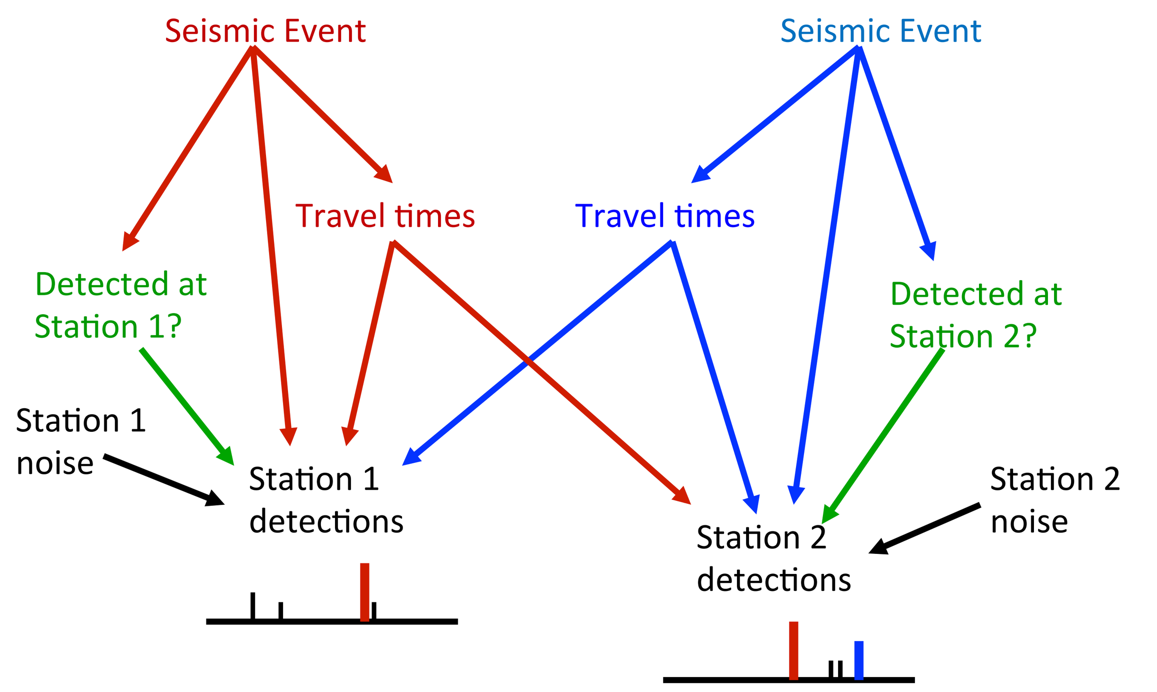
where f (signal) = set of all detections

Signal-based Bayesian monitoring:

P(world | signal) ~ P_ϕ(signal | world) P_ϕ(world)

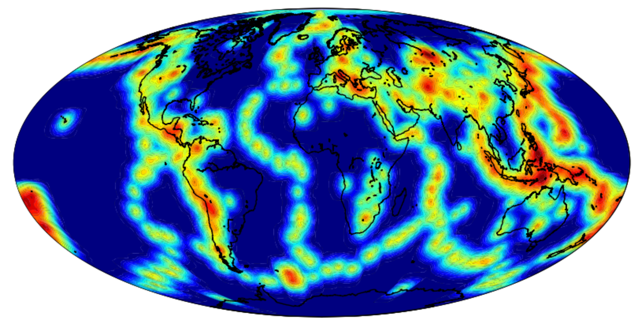
Background: Detection-based Bayesian monitoring

NET-VISA is a probabilistic generative model of seismic events, their propagation and detection. Also, a model of noise detections.



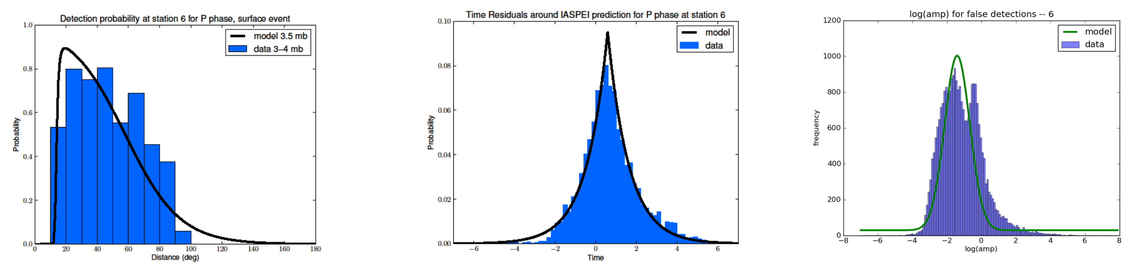
The model consists of various probability distributions, which include:

• A distribution for seismic event locations, which includes natural seismicity and manmade seismicity (assumed uniform).



• The detection probability of an event depends only on event magnitude, depth, and distance to station.

• The residual distribution for the travel time, azimuth, and slowness are mostly modeled as Laplacian distributions.



Results on one week of data (trained on 2.5 months)

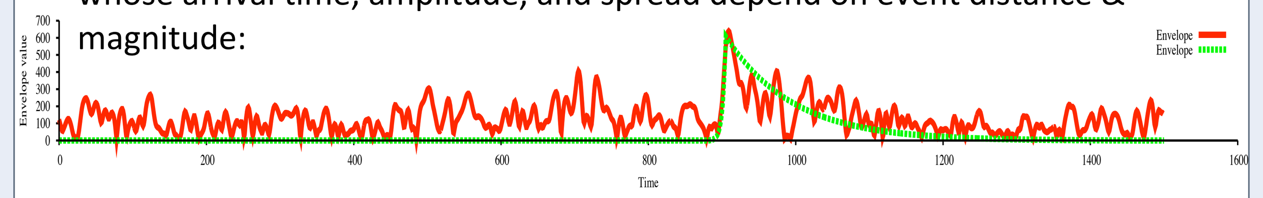
m_b range	Number of Events	SEL3		NET-VISA	
		Recall (%)	Error (km)	Recall (%)	Error (km)
0-2	74	64.9	101	86.5	101
2-3	36	50.0	186	77.8	159
3-4	558	66.5	104	86.4	115
>4	164	86.6	70	93.3	78

Signal-based Bayesian monitoring

• A signal-based model encodes the joint distribution of the waveform traces at each station given the event parameters for all hypothesized events.

• We overlay background noise models, independent for each station, with event-generated waveforms of the contributions of each phase type.

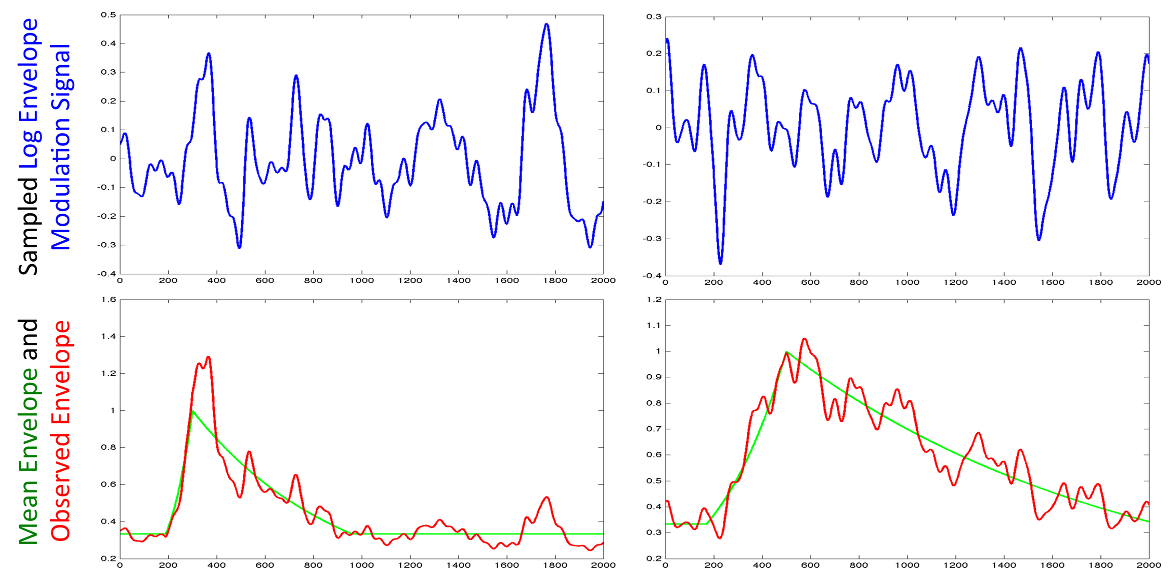
• A simple approach involves a low-dimensional parametric envelope descriptor (e.g., triangular or paired-exponential, cf. Huseby et al., 1998) whose arrival time, amplitude, and spread depend on event distance & magnitude:



• Actual envelopes are not well-modeled by template + iid noise. We model large-scale variation in envelope shape as the product of a mean envelope (magnitude and distance dependent), and a stochastic modulation signal:

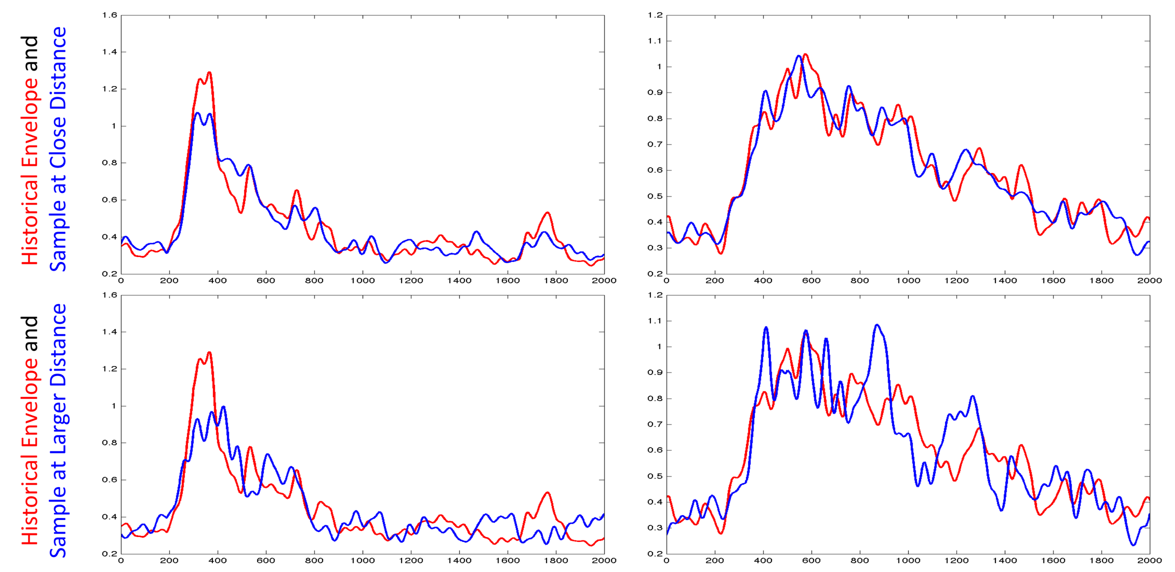
observedEventEnvelope = meanEnvelope x exp(eventSpecificModulation)

• A simple modulation model, which we will ultimately learn from historical data, is based on a random linear combination of Fourier basis functions:



• A basic model of envelope variation would assign each event an independent sampled log-modulation signal, using a Gaussian prior on the basis coefficients

• Envelope (or waveform) shape is highly repeatable across events with the same location and type. A nonparametric extension, based on *Gaussian processes*, captures correlations among event envelopes that decay with distance (analogous to *correlation matching*).

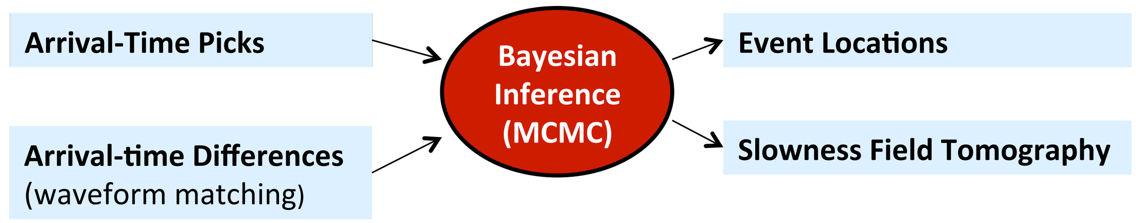


• The rates at which correlations decay with distance will also be calibrated from historical training data.

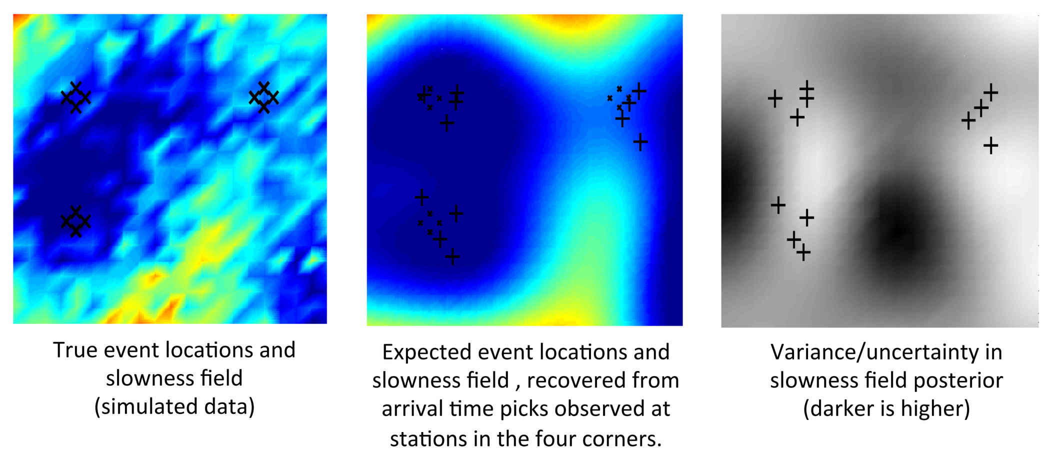
Bayesian Double-Differencing

• The method of *Double-differencing* (Waldhauser & Ellsworth, 2000) relocates events using precise arrival-time difference information obtained through waveform matching, while considering correlated travel-time residuals.

• We formulate a **Bayesian model** with similar properties: our model *integrates information* from picked arrival times as well as arrival-time differences, and *explicitly models correlated residuals* as a function of variation in the underlying slowness field (Rodi and Meyers, 2007):



• The slowness field is modeled as a *Gaussian process*, which induces an equivalent Gaussian process on the travel-time residuals. This connection allows inference to recover a posterior distribution over event locations as well as the slowness field:



True event locations and slowness field (simulated data) | Expected event locations and slowness field, recovered from arrival time picks observed at stations in the four corners. | Variance/uncertainty in slowness field posterior (darker is higher)

• Inference is through Markov Chain Monte Carlo (Metropolis-Hastings w/ Gaussian proposals).

• Bayesian/probabilistic formulation makes it easy to include additional inputs, such as arrival-time differences from waveform matching / cross-correlation techniques.

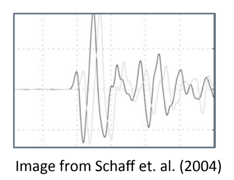
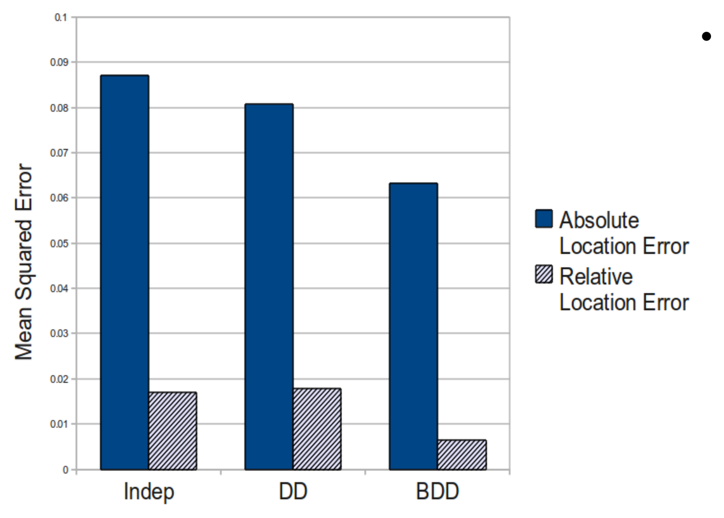


Image from Schaff et. al. (2004)



• Results on simulated data show decreased error in both absolute and relative event locations, as compared to double-differencing and to a baseline inversion which assumes independent residuals.

CONCLUSIONS

• Prior results suggest that Bayesian monitoring is a promising technique for analyzing streams of parametric detections from multiple stations to form a global event bulletin and may be preferable to existing deployed methods for global association.

• Our current work, in its very early stages, is aimed at extending Bayesian monitoring with generative models of waveform envelopes to improve detection and association and performing joint inference of event locations and slowness fields to improve localization accuracy.

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