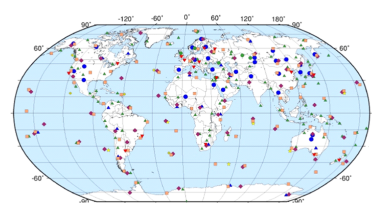
SIG-VISA: Signal-Based Vertically Integrated Bayesian Monitoring

David A. Moore[1], Alex Ning Ding[1], Kevin Mayeda[1], Stephen C. Myers[2], Stuart J. Russell[1]

University of California, Berkeley[1] and Lawrence Livermore National Laboratory[2]

Introduction

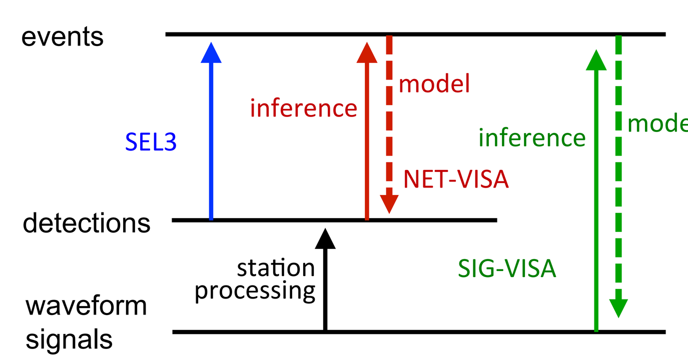
- **Global seismic monitoring** aims to recover the time, location, depth, and magnitude for all seismic events worldwide.
- We propose a new approach to monitoring, using Bayesian inference in a **joint statistical model of seismic events and seismic signal traces**, with the goal of improving event detection and localization.
- Our system is currently trained and evaluated on data from the **International Monitoring System (IMS)** established by the **Comprehensive Nuclear-Test-Ban Treaty (CTBT)**.



IMS network: Blue dots and triangles are primary seismic stations.

- The IMS's current automated system (**SEL3**) detects 69% of real events and creates twice as many spurious events.
- Human analysts find more events, correct existing ones, throw out spurious events, and generate the **LEB** reference bulletin, considered reliable for events above magnitude 4.0 (about 1 kiloton).
- NET-VISA is a *detection-based* Bayesian monitoring system whose performance is limited by the classical, bottom-up, threshold-based detection algorithms used in station processing. *It misses about 2-3 times fewer events than SEL3.*
- SIG-VISA, a *signal-based* system, uses generative models that span the range from events to waveform traces. This approach has several qualitative advantages over NET-VISA, with the potential for significantly improved sensitivity and localization performance.

Signal-Based vs. Detection-Based Monitoring

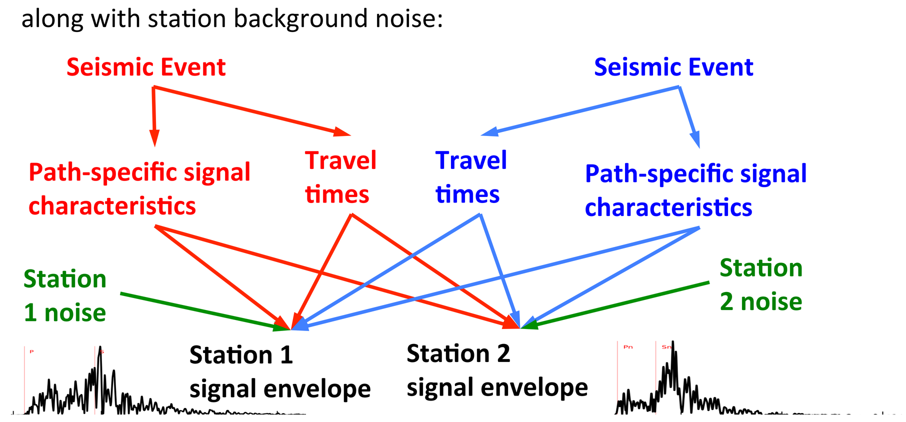


Bayesian monitoring with a generative approach:
P_θ(world) describes prior probability for what *is* (*events*)
$P\phi$(signal | world) describes forward model (propagation, measurement, etc.)

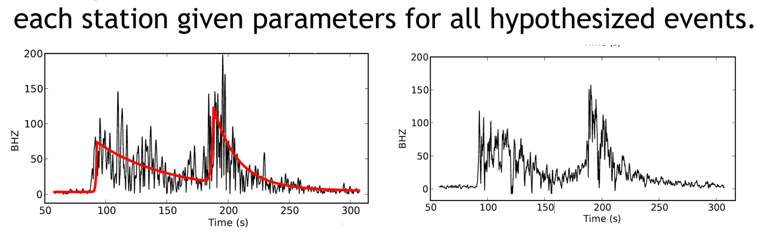
Detection-based Bayesian monitoring:
$P(\text{world} \mid f(\text{signal})) \propto P_\phi(f(\text{signal}) \mid \text{world})\, P_\theta(\text{world})$
where f(signal) = set of all detections
Signal-based Bayesian monitoring:
$P(\text{world} \mid \text{signal}) \propto P_\phi(\text{signal} \mid \text{world})\, P_\theta(\text{world})$

Signal Envelope Model

SIG-VISA is a probabilistic generative model of seismic event origins, propagation, and observed waveform envelopes, including event signals along with station background noise:



The signal model encodes a distribution over waveform envelopes at each station given parameters for all hypothesized events.

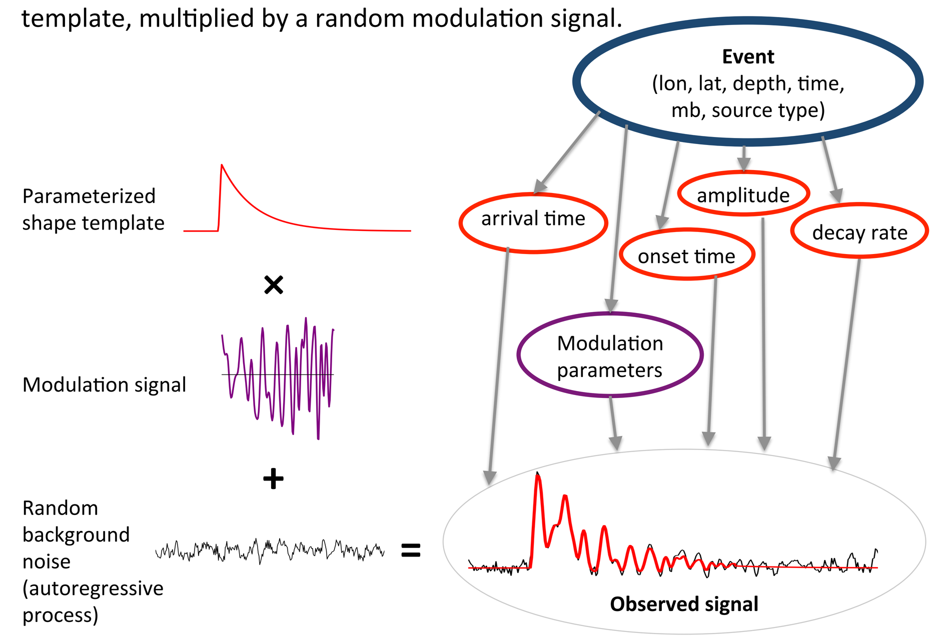


Left: An observed envelope showing the P and S arrivals and subsequent coda decays. The red line indicates the template fit.

Right: A synthetic envelope generated from the template with an autoregressive modulation process.

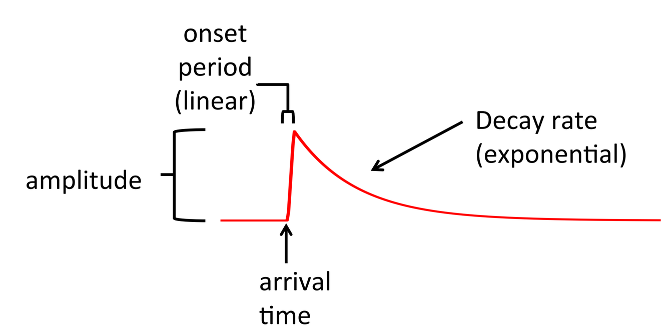
Phase Envelope Model

Each arriving phase is modeled as a parameterized shape template, multiplied by a random modulation signal.

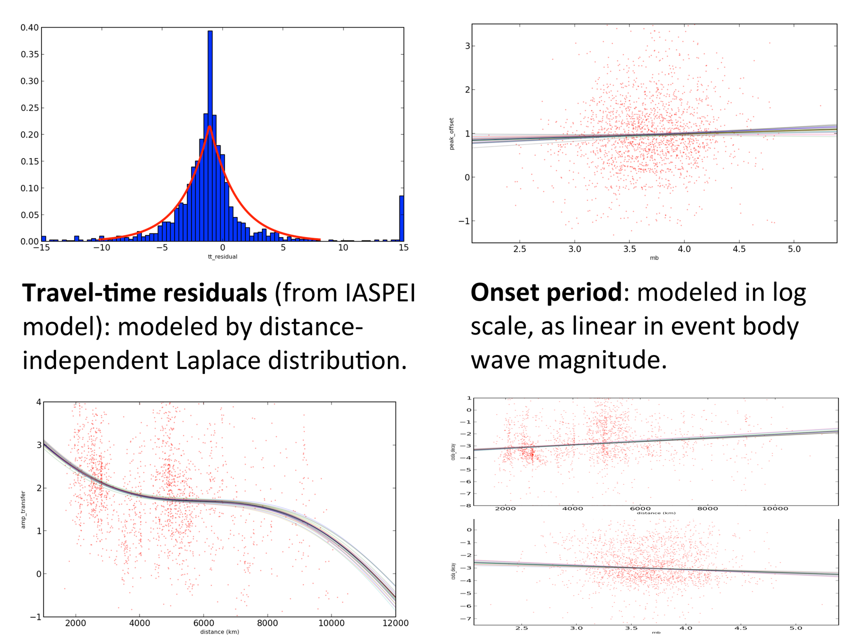


Shape Parameter Models

Shape templates are described by four parameters:



These parameters are modeled, conditioned on an event hypotheses, by a combination of *physical* and *probabilistic* models. The probabilistic models combine simple *parametric* relationships along with a *nonparametric* (Gaussian process / kriging) component to capture local structure.

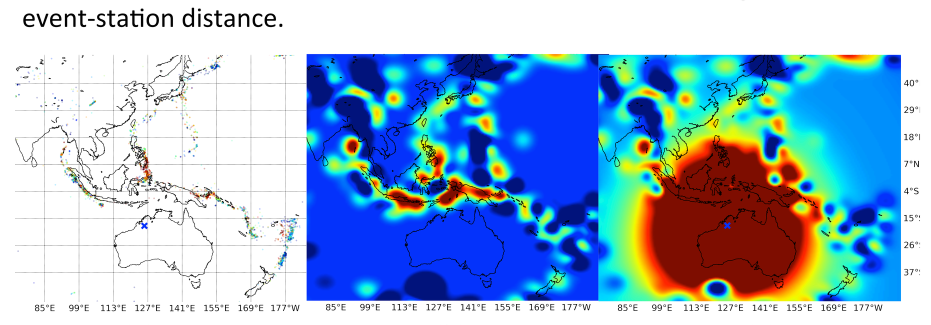


Travel-time residuals (from IASPEI model): modeled by distance-independent Laplace distribution.

Onset period: modeled in log scale, as linear in event body wave magnitude.

Amplitude transfer function (from Brune/Mueller-Murphy source model): modeled as nonlinear in event-station distance.

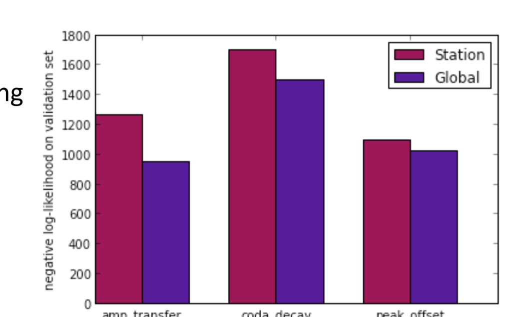
Coda decay rates: modeled in log scale, as linear in event-station distance *and* event magnitude.



(a) (b) (c)

Above: nonparametric Gaussian process (kriging) model of amplitude transfer function. a) Training events colored by transfer function, b) basic kriging model, c) hybrid model combining local structure from kriging with the overall distance-decay relationship from parametric regression.

Parametric components are modeled *hierarchically*, constraining the models at individual stations towards a latent global prior. **Right:** improvements in log-likelihood on a validation set from the global hierarchical model, compared to a per-station model.



Sensitivity

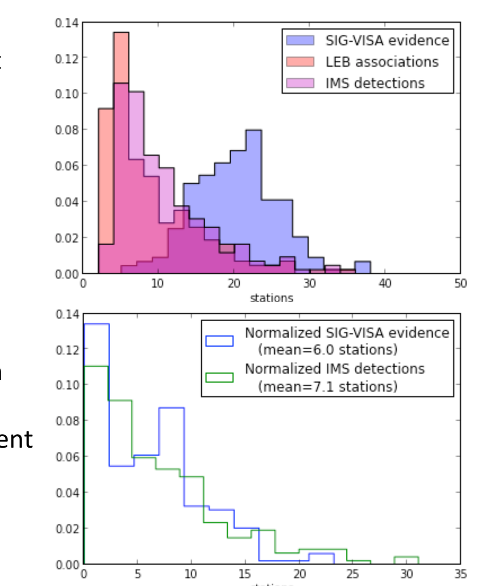
A station provides *statistical evidence* for an event if its signal is more probable under the hypothesis of that event than under a noise model.

(10, 50, 90th) percentiles of the # of stations yielding detections/evidence at time of P wave arrival (using vertical channel, 2-3Hz signals), across 212 test events with $m_b \in [3.5, 4.0]$:

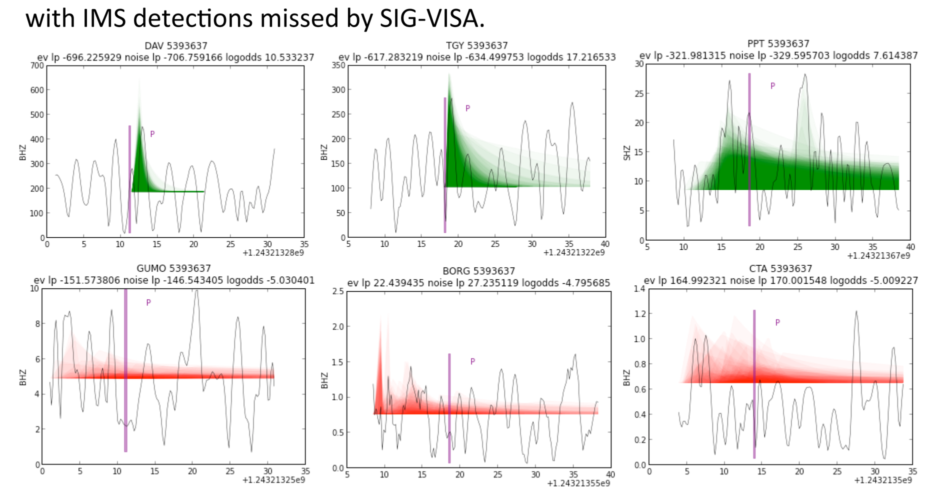
- IMS detections: 4, 9, 19
- SEL3 associations: 2, 4, 13
- LEB associations: 3, 6, 17
- **SIGVISA: 14, 20, 27**

Normalized associations: associations in excess of the 'base rate' (expected # of associations from a random artificial event hypothesis in same m_b range).

- IMS detection base rate: 3.0
- SIG-VISA evidence base rate: 14.8



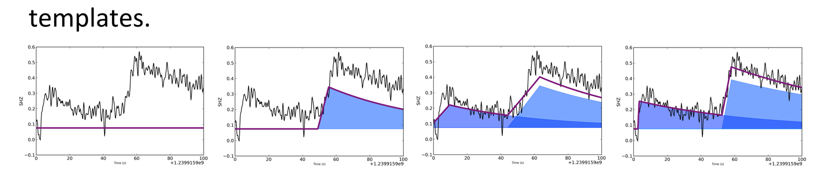
2009 DPRK event: SIG-VISA finds statistical evidence for P arrivals at 53 stations, vs 42 stations with IMS detections. **Top:** examples of stations providing statistical evidence, but with no IMS detection. **Bottom:** stations with IMS detections missed by SIG-VISA.



Inference

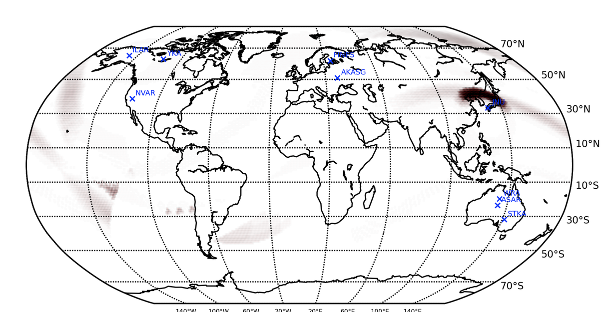
SIG-VISA uses Markov Chain Monte Carlo (MCMC) to sample from the posterior distribution over event hypotheses conditioned on observed signals. Move types include:

- **Template parameter moves** tweak the shape parameters describing a template to better match the signal.
- **Event attribute moves** modify the location, depth, time, and magnitude of an event hypothesis to better fit the templates associated with that event at stations across the network.
- **Template birth/death/split/merge moves** create and destroy shape templates, not associated with any particular event phase, to explain a signal spike. New templates are proposed with probability proportional to the height of the observed envelope, minus envelopes from all current templates.



Example of template birth moves finding an explanation for an observed signal. The final frame shows the result after several additional template parameter moves.

- **Event birth/death moves** propose new hypothesized events to explain unassociated templates.
  - Event locations are proposed by Hough transform, using a 3D (lon, lat, time) accumulator array.
  - Weights of accumulator bins are sums of "votes" from all current unassociated templates; each template votes for all bins in its backprojected space-time cone.



Hough accumulator array showing proposal density centered on the Korean peninsula.

Newly-born events generate templates for all appropriate phases at all stations. These templates replace unassociated templates with probability

$$p(\text{associate } T_i) \propto \frac{p_{E,P}(T_i)}{p_U(T_i)}$$

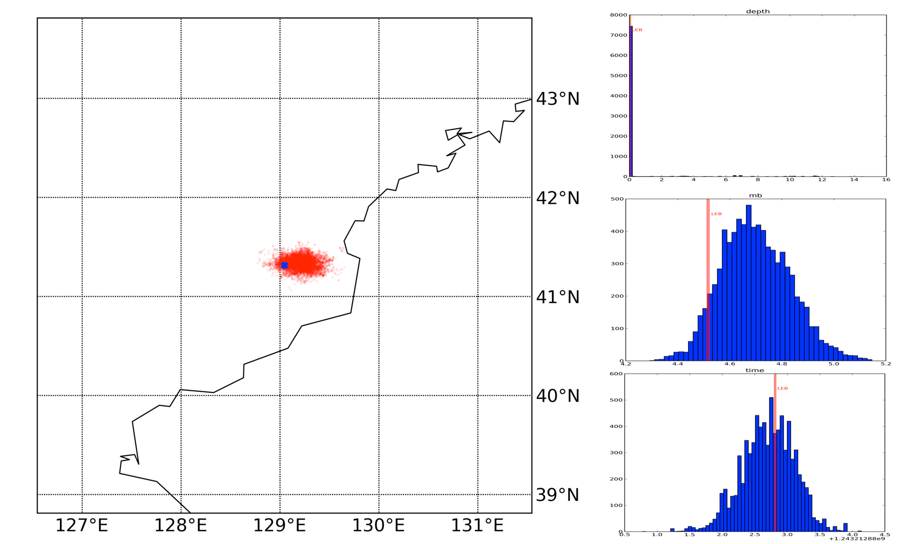
or are created anew with probability $p(\text{create } T) \propto 1$.

When an event is killed, its generated templates are similarly either killed or retained as unassociated templates.

Localization: 2009 DPRK Event

Using a network of 105 stations, and a restricted model (only P/Pn phases, 2-3Hz frequency band, using only the reference station at each array), we infer a mean location of 129.20° E, 41.33° N for the 2009 DPRK test, **13 km** from the REB reference location.

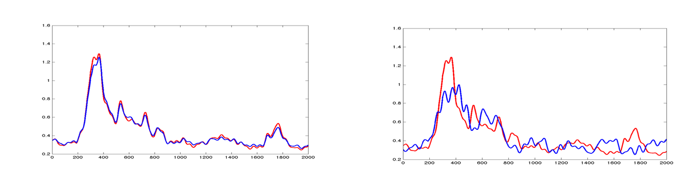
Below: *(left)* Posterior location density from 10000 MCMC samples, with REB location marked in blue. *(right)* Samples showing posterior uncertainty in origin depth, magnitude, and time.



Probabilistic Waveform Matching

Waveform shape is known to be **highly repeatable** across events with the same location and source mechanism (Thorbjarnardottir and Pechmann, 1987; Harris, 1991).

SIG-VISA captures this effect by replacing the independently sampled modulation signal with a signal **conditioned on the event location**, causing nearby events to generate correlated waveforms:

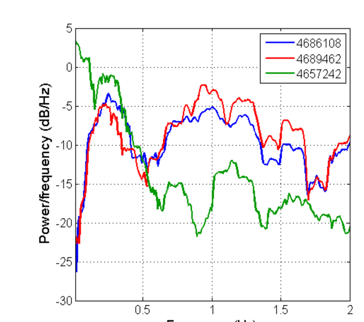


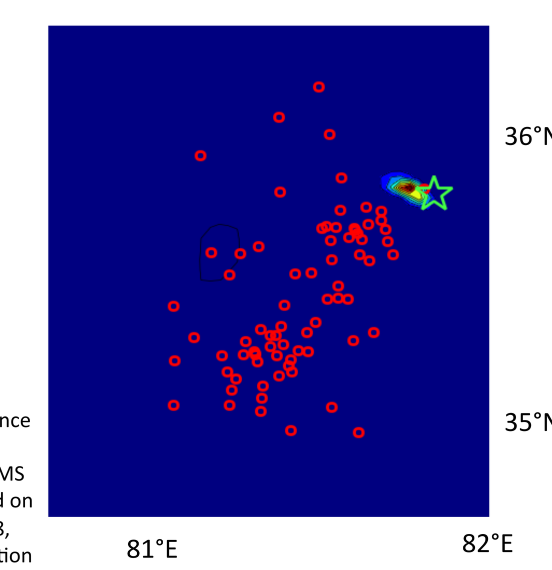
Synthetic reference envelope (red) and a sampled envelope (blue) from a Gaussian-process generative model for a nearby event location.

The same reference envelope (red) and a sampled envelope (blue) from a distant event location.

This causes a statistical "waveform matching" effect to emerge from inference in the probabilistic model.

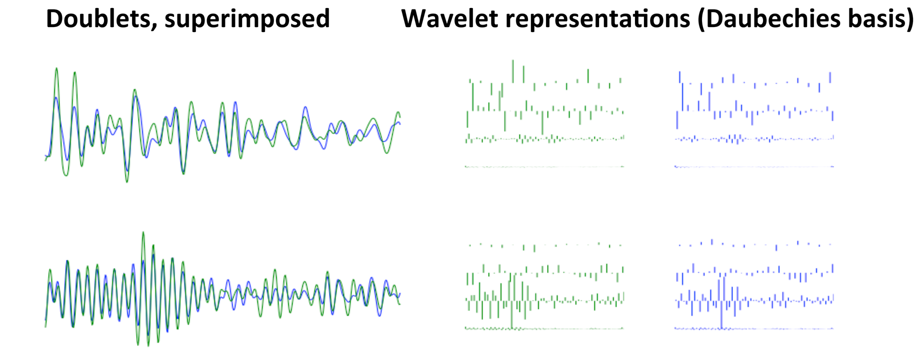
Modulation signals are represented parametrically as a **sum of basis functions** (e.g. Fourier or wavelet basis), with coefficients modeled by a spatial Gaussian process.





Above: power spectra for three waveforms from an aftershock sequence in Tibet, showing a doublet pair.
Right: Posterior location density for IMS event 4689462, using a model trained on signals including the doublet 4686108, peaking 8km from the reference location (green star).

Wavelet signal representations retain time-domain locality, allowing for greater modulation uncertainty in later parts of the signal, as the signal approaches the noise floor, while maintaining a compact representation. We are currently exploring probabilistic models of wavelet representations.

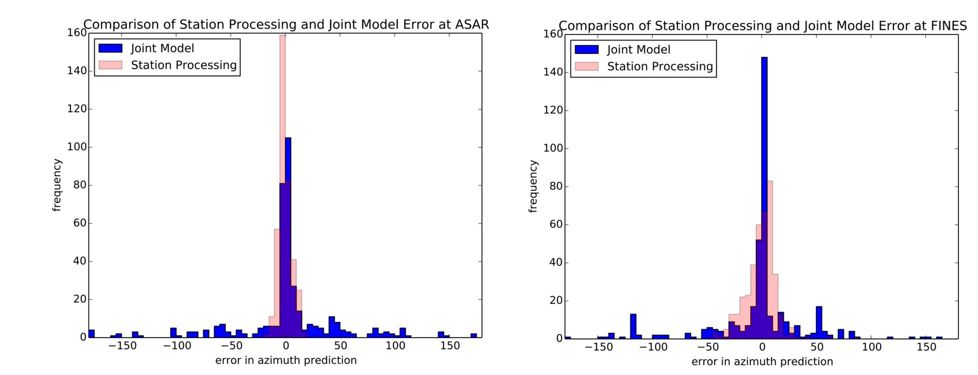


Modeling Array Stations

Our standard model assumes that signals are independent at each station, conditioned on event attributes, but this is false for signals at array elements, which are empirically correlated. We remove the independence assumption by jointly modeling each template parameter across array elements with a single Gaussian process (GP), thus extending the existing 3D event location space to a 6D station-event pair.

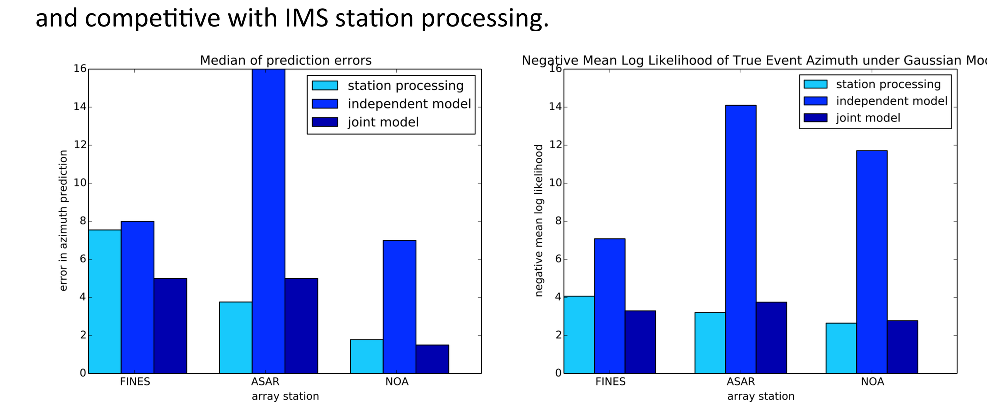
Points in the 6D space are correlated by a squared-exponential covariance function defined by four length scale parameters: surface distance length scale for station and event, and depth/elevation length scales for station and event. We learn the optimal length scales for each GP by gradient ascent on the marginal likelihood of the training data.

To evaluate the effectiveness of the joint array model, we perform 'probabilistic beamforming' for new events using 2-3Hz filtered signals from all array elements: we compute the event azimuth having highest posterior probability under the model, conditioned on the signals at array elements.



Above: histograms comparing the errors in modal azimuths from the SIG-VISA joint array model, with the errors in azimuths recorded by IMS station processing at two arrays, FINES and ASAR. The SIG-VISA model gives a sharper peak around 0 error than IMS station processing at FINES, though not at ASAR. In both cases it produces more large errors than IMS station processing.

Below: comparisons of the joint array model to IMS station processing and to the independent array model, comparing the median error in predicted azimuth as well as likelihood of the reference azimuth. Likelihoods for the station processing were approximated by a Gaussian fit to the residuals. The joint array model is a significant improvement over an independent model, and competitive with IMS station processing.



Conclusions

- Bayesian monitoring provides a **unified framework** for a modular, next-generation monitoring system, integrating physics-based seismological models with probabilistic reasoning for principled handling of noise and uncertainty.
- Explicit modeling of seismic signals **eliminates detection threshold effects** and allows incorporation of detailed signal features.
- Preliminary results are competitive with existing systems; we expect performance to improve as inference is scaled up and model extensions (array stations, multiple phase types, improved models of modulation signals) are incorporated.
- Nonparametric spatial models of signal modulation enable the **unification of waveform cross-correlation methods** with an end-to-end monitoring system.

Acknowledgements

We gratefully acknowledge the support of DTRA for this work under Basic Research Grant #HDTRA-11110026, as well as the support of the CTBTO through the provision of IMS data and the use of the vDEC experimental platform.

References

Arora, Nimar S., Stuart J. Russell, Paul Kidwell, and Erik Sudderth, "Global seismic monitoring as probabilistic inference," In *NPIS 23*, MIT Press, 2011.

Mayeda, K., Hofstetter, A., O'Boyle, J.L., and Walter, W.R. (2003). Stable and transportable regional magnitudes based on coda-derived moment-rate spectra. *Bulletin of the Seismological Society of America*, 93(1), 224-229.

Myers, S.C., G. Johannesson, and W. Hanley (2007). A Bayesian hierarchical method for multiple-event seismic location. *Geophys. J. Int.*, 171, 1049-1063.

Schaff, D. P., Bokelmann, G. H. R., Ellsworth, W. L., Zanzerkia, E., Waldhauser, F., & Beroza, G. C. (2004). Optimizing Correlation Techniques for Improved Earthquake Location. *Bull. Seism. Soc. Amer*, 94(2), 705-721.

Thorbjarnardottir, B. S. and J. C. Pechmann (1987). Constraints on relative earthquake locations from cross-correlation of waveforms. *Bull. Seismol. Soc. Am.*, 77, 1626–1634.