Elastic Bayesian Model Calibration

Calibrate the aligned data and shooting vectors using the following model

$$\tilde{z}(t, \mathbf{x_i}) = \tilde{y}(t, \mathbf{x_i}, \theta) + \delta_{\tilde{y}}(t, \mathbf{x_i}) + \epsilon_{\tilde{z}}(t, \mathbf{x_i}), \quad \epsilon_{\tilde{z}}(t, \mathbf{x_i}) \sim \mathcal{N}(0, \sigma_{\tilde{z}}^2)$$

$$\mathbf{v}_{z \to z}(\mathbf{x_i}) = \mathbf{v}_{y \to z}(\mathbf{x_i}, \theta) + \delta_{\mathbf{v}}(\mathbf{x_i}) + \epsilon_{\mathbf{v}}(\mathbf{x_i}), \quad \epsilon_{\mathbf{v}}(\mathbf{x_i}) \sim \mathcal{N}(0, \sigma_v^2 \mathbf{I})$$

Note: The shooting vector will be identity if the data is aligned to the observation (experiment)

Then if θ is calibrated correctly the shooting vectors will be identity

MCMC Sampling

For each experiment the likelihood is a Gaussian likelihood

1. We fit an emulator (Gaussian Process, BASS, MARS) to the simulated data
2. Uniform priors on θ
3. Sample posterior using delayed rejection adaptive Metropolis Hastings
4. Implemented using Impala (LANL) or Dakota (SNL) calibration framework