Multi-resolution seismic tomography maps fusion with probability graphical models near the 2019 Ridgecrest area
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Abstract
The resolution of velocity models obtained by tomography varies due to the inversion approach, ray coverage, etc. Fusing such tomography models with different resolutions is desired when updating community models, to enable more accurate ground motion simulations. Toward this goal, we propose a novel approach to fuse multi-resolution seismic tomography maps with probability graphical models (PGMs). We present the relation between subdomains with multiple resolutions, in terms of high-resolution (HR) and low-resolution (LR) components. To evaluate the efficacy of the proposed PGM fusion method, we employ the model on both synthetic checkerboard models and a fault zone structure imaged from the 2019 Ridgecrest, CA, earthquake sequence. The Ridgecrest fault zone image consists of shallow-scale (top 1 km) high-resolution surface wave models obtained from ambient noise tomography, which is embedded into the SCEC Community Velocity Model (CVM) version 5.27-M01. The proposed PGM fusion method can merge any type of gridded multi-resolution velocity model and has the potential to become a valuable tool for computational seismology.

Motivation and Objective
• Combining the models with different resolutions is an essential step for updating the community models.
• A direct merging will preserve the sharp changes on the boundary areas (a2), while a strong smoothing will lose the detailed information from HR models (a3-a4).
• We proposed a probability graphical model to adaptively balance the trade-off between smoothness and sharp details.

Markov Random Field
A Markov random field is a set of random variables having a Markov property described by an undirected graph [3], which belongs to the family of probability graphical models (PGMs). This method can consider the geometry property and balance the smoothness and the details information (sharpness) in images.

Let \( a_i \) be the observed velocity value (continuous), and \( x_i \) be the hidden label (discrete). We assume \( a_i \) follows the distribution approximated by weighting the Gaussians from the neighborhoods \( \{w_i \} \) is the weight variables), so that we can have:

\[
a_i \sim \sum_{w_i \in \text{neigh}(i)} w_i \mathcal{N}(a_i, \sigma_i)
\]

\( x_i \in \{1, \ldots, N\} \)

\( a_i \) and \( x_i \) can be updated iteratively through an Expectation–Maximization algorithm.

Results

Table 1. Synthetic sensors (X) are placed in the boundary areas to calculate travel time residuals. We use multiple metrics to evaluate our tomography model fusion results: travel time Residual Mean-Squared-Error (RMSE), which measures how much information is lost after model fusion. Perception based Image Quality Evaluator (PIQE), a commonly used measurement for image quality [5], and Peak Signal-to-Noise Ratio (PSNR, which measures the sharpness of images). Our PGM method preserves more detailed information than direct Gaussian smoothing.

Conclusion and Future Work
• Our PGM-based tomography model fusion method achieves a balance between smoothing the undesired sharp boundary and preserves the detailed information from the HR models.
• Currently, we assume that similar pixels (pixels sharing the same mask label) follow the same distribution. We believe that other physical and seismological information (such as uncertainty and ray-path density) can also be informed. Hopefully, they will give a better interpretation of the fusion results.

References

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