

Chapter 6

Conclusions

This thesis has focused on using nonstationary prediction-error filters in multidimensional interpolation. Where it innovates is in how the prediction-error filters are generated, the domain in which they operate, and the sampling of the data being interpolated. I developed three distinct approaches that are catered to irregularly-sampled data, data with large near-offset gaps, and the large amount of multidimensional interpolation required for 3D prestack marine data.

Most approaches to interpolating irregularly-sampled seismic data are transform, moveout, or migration-based approaches. I addressed the problem of irregularly-sampled data with prediction-error filters by using multiple regridded copies of the data to estimate a PEF. This method performed reasonably well on stationary synthetic data, and also on the spatially-variable quarter-dome data. Both of these datasets are relatively low-frequency and were randomly sampled. When this method was applied to field 2D land data, the performance was acceptable, but the acquisition of these data was far from random. One obvious improvement to this method would be to automatically choose optimal scales on which to estimate the PEF and to weigh data in the estimation based on how well they are characterized at each scale.

I conclude from these experiments that while theoretically pleasing, randomly-sampled synthetic data do not serve as a particularly useful analogue for most irregularly-sampled field data. Field data are typically sampled along tracks with deviations therefrom, be it the source lines and receiver cables for a 3D land survey or the smoothly varying sail lines and receiver cables of a marine survey. Both land and marine data are plagued by large gaps and undersampled axes, not random sampling along all spatial axes.

One such large gap in marine seismic data is a near-offset gap between the towed source and the nearest receiver, a problem usually addressed by normal-moveout or a Radon-transform-based interpolation. Instead of using information from the nearby primaries as in a Radon or an RMS-velocity-based method, I generated pseudoprimaries by using active-source interferometry, in which all receivers are crosscorrelated for each shot so that the correlation of primaries with free-surface multiples creates pseudoprimaries with a virtual source location at one of the receivers. These data are generated at a wider range of offsets than the original recorded data, including the near-offset information absent from the original recording. I used these pseudoprimaries as training data for nonstationary PEFs, both in time and space and in frequency and space.

This method of interpolating the large near-offset gap using a PEF estimated on pseudoprimaries works well on synthetic data, where I introduce a large gap, for the most part correctly reconstruct the missing data. The benefit of using PEFs in this process is that spurious events that do not correspond to a correlation between a multiple and a primary are often removed from the result, the squared wavelet of the pseudoprimaries is ignored, and the signal-to-noise ratio of these near offsets considerably improves. While the method works well on synthetic data, it had somewhat less success with the field data. Illumination issues with the multiple reflections also appear in the pseudoprimaries, causing steeply-dipping reflections to be comparatively weak in amplitude. Many of the methods used in signal/noise separation could be helpful here, as the training data used contain both coherent signal and coherent and incoherent noise.

While this method works well in 2D scenarios, the prospects for 3D are limited by the limited source distribution in the crossline. Much as with both 3D SRME and passive interferometric methods, pseudoprimary generation is highly dependent upon adequate source coverage. With the advent of wider-azimuth marine data, the prospects for keeping this method strictly data-driven improve, although the need for it may decrease.

The last chapter of this thesis is the most practical. The jump from 2D to 3D SRME methods requires a large amount of data to be created, both extrapolated and interpolated. Most 3D SRME implementations rely upon moveout or partial prestack migration operators to generate these data along the inline source, crossline source, and crossline receiver axes. I introduce nonstationary frequency-space interpolation, where the assumption in Spitz interpolation is used with nonstationary multidimensional prediction-error filters to interpolate data in anywhere from two to five dimensions. I first compare a nonstationary PEF-based methods applied frequency-by-frequency in different domains with different dimensionalities for a synthetic dataset, and conclude that for inline source interpolation, a strictly inline approach produces the best result. Meanwhile, a source-by-source 3D interpolation of receiver cables gives slightly better results than does a full 4D approach.

With this nonstationary frequency domain approach to field data with only four cables, the inline source interpolation is again best solved as a strictly inline problem, while the crossline receiver interpolation produces mixed results. A 4D interpolation produces a more robust result while a 3D shot-by-shot interpolation produces a more detailed result that is more easily compromised by noise.

Finally, iterating inline source interpolation with crossline receiver interpolation is able to produce data at densities required for 3D SRME. The drop in quality of the data is not so much caused by the assumption of previously interpolated data as known data, but more the jump in difficulty from inline-source to crossline-receiver interpolation. I conclude that interpolating many of the large factors of data required for full prestack interpolation is possible using prediction-error filters, in part because the interpolation takes place along multiple axes, so the assumptions behind the

interpolation are less stretched.

This thesis has been based upon the idea of using a nonstationary PEF as a container for useful information from training data that are not good enough to directly substitute for missing data. I have made three choices of training data, all that approximate the data differently. The choice of training data should be considered specific to the task at hand, both in terms of the character of the data in question and the sampling of that data, and is an open framework for use in many other situations.