Combining arrival classification and velocity model inference

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When employing a mineral systems approach to exploration, understanding the crustal scale architecture is a key requirement. In practice this means we are interested in inferring crustal scale architecture i.e. structural boundaries, among them the crust-mantle boundary and depth of sedimentary basins from geophysical data. Active seismic data is among the most informative datasets on the crustal scale: over a number of years, Geoscience Australia (GA) has led an extensive active seismic acquisition campaign that has resulted in multiple seismic transects across the continent (Kennett et al., 2013) that contain valuable information. While there have been some targeted efforts (Fomin and Goleby, 2006), the broad application of seismic travel time tomography for velocity model building in support of the inference of crustal scale architecture has not kept pace with the release of these high-quality datasets. Harvesting the information contained in these data through travel time tomography typically requires manually picking arrivals and classifying them. This is inevitably a time consuming, subjective, and iterative process, and vulnerable to a mis-identification of arrivals and subsequent incorrect recovery of structure.

We propose to treat arrival identification and velocity model inference as a joint problem. In this approach, we seek to classify a set of potential arrivals into noise and ray theoretical arrivals in a way that is self-consistent with the evolving velocity and structure model. To achieve this, we employ an expectation-maximization algorithm (Dempster et al., 1977) where, in the expectation step we update the classification of the arrivals, and in the maximization step we update the velocity model. By iteratively applying the two steps to convergence we arrive at a maximum a-posteriori estimate for the velocity model, and simultaneously, probabilities for the classification of the potential arrivals that were postulated using an auto-picker.

In the context of arrival uncertainty, the dominant source of uncertainty is whether an auto-picker identified arrival is ray-theoretically plausible or not, and, if it is, which ray path it is representative of. A synthetic example is used to illustrate the performance of the proposed algorithm and demonstrate its ability to capture this dominant source of uncertainty when compared to the uncertainty related to the arrival time of a given pick. We will also discuss how the algorithm performs when the identified but not yet classified arrivals are affected by significant noise, i.e., the travel times assigned to them are incorrect. Our synthetic results show that both types of data uncertainty need to be accounted for to prevent inversion from producing an incorrect inference of the true subsurface velocity and structure, including an over- or under-estimation of uncertainty.

Finally, we conclude by illustrating the practical feasibility and benefits of treating arrival or phase classification as an integral part of a velocity model building by presenting the results of a 1D synthetic application and discussing the applicability of the methodology to representative shot gathers.

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