QUANTIFYING UNCERTAINTY IN AVA INVERSION USING DEEP LEARNING

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ABSTRACT

Conventional prestack seismic inversion for elastic properties is limited by the resolution of the time domain seismic signals, which in general, is not adequate to capture all features presented in the recorded well logs in depth domain. One possible solution is to map the resolution discrepancy into probability distributions to examine all what-if scenarios from the well log responses, and use those to constrain the inversion process. This research introduces a novel approach implementing a multimodal deep learning structure to predict the posterior distributions of the subsurface elastic properties from seismic gathers without the need of the heuristic calculation of the partition function. The algorithm bypasses the assumption of the forward modelling steps, which usually include the convolution model and linearized Zoeppritz equation, to relate the target models to the observed data. Thus, it has the potential of inverting depth domain seismic gathers. Besides, unlike the common deep learning structure for prestack inversion, the new design does not require combination and reorganization of the impedances and density logs into one single layer, but allows them to be input to the system at separate branches. To further improve on the features in capturing the hidden relationships, the seismograms are processed with a continuous wavelet transform to generate training data. The algorithm is applied to two datasets: the synthetic angle gathers generated from some elastic models using the three-term approximation to examine the network stability, and the field angle gathers with limited well coverage to demonstrate its application in real noisy data.

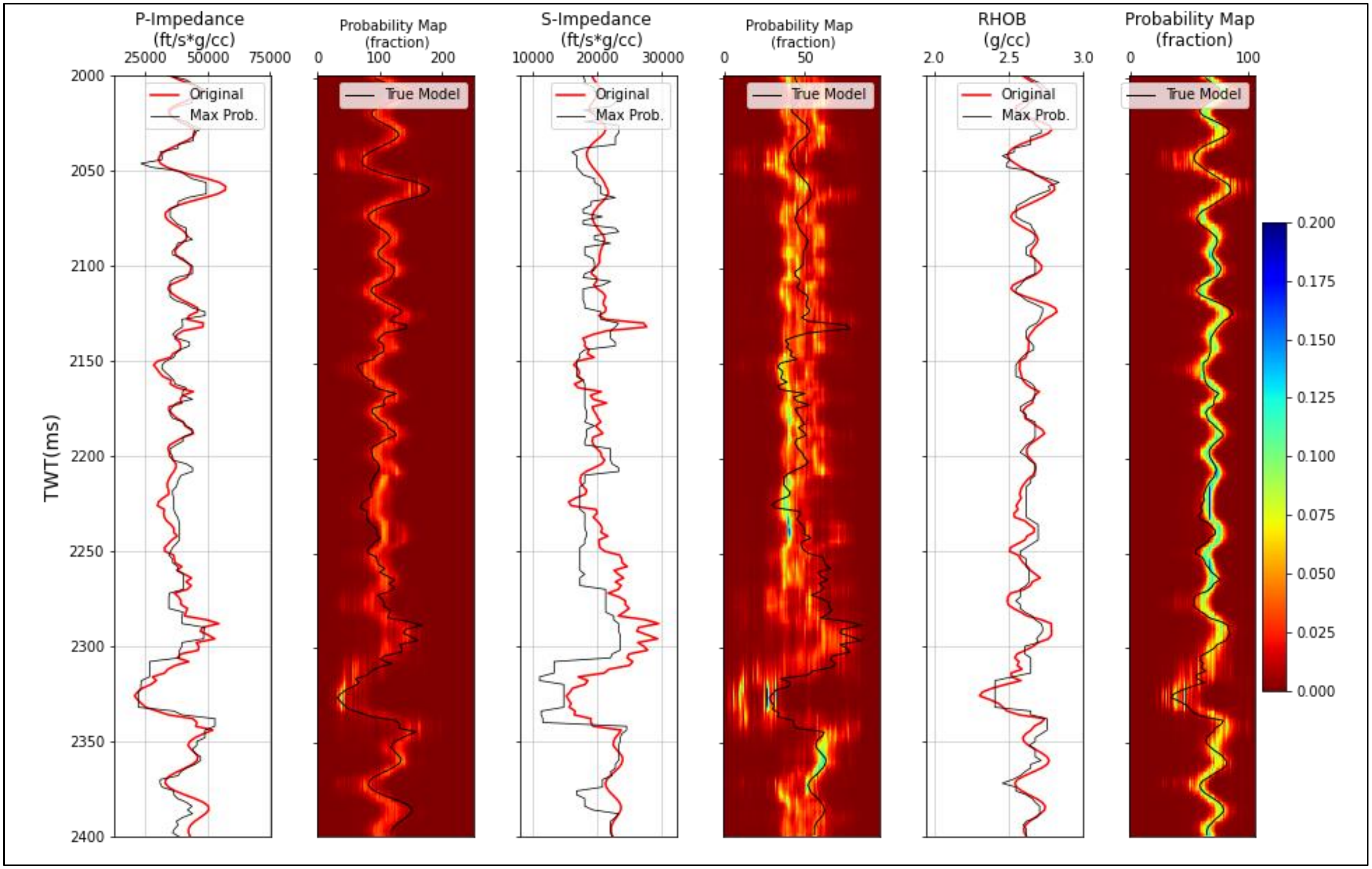

Figure: The network predictions at blind test well in comparison with real log. The representative predicted log curves correspond to maximum probability values. The predicted posterior distribution map covers the true model, which suggests that the network well performs in this dataset.