A BOLTZMANN MACHINE FOR HIGH-RESOLUTION PRE-STACK SEISMIC INVERSION

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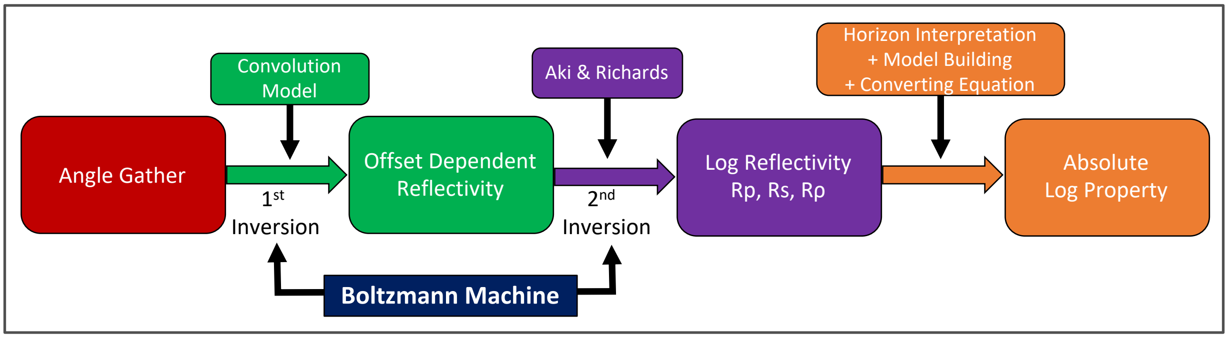
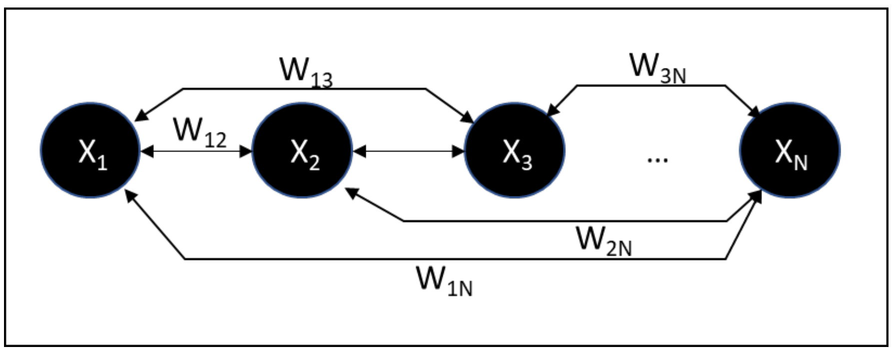
ABSTRACT

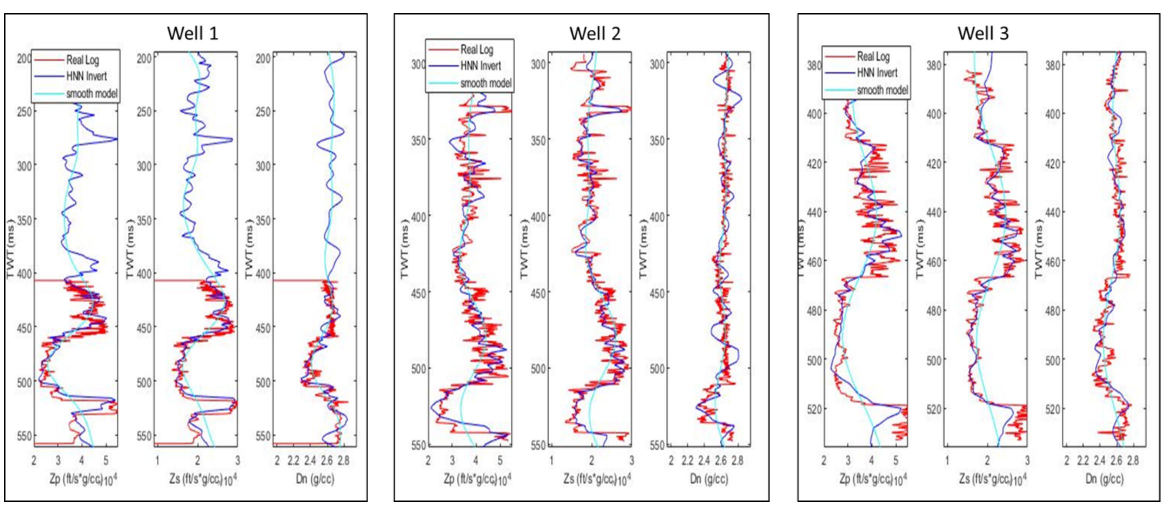
Seismic inversion is one popular approach that aims at predicting some indicative properties to support the geological interpretation process. The existing inversion techniques show weaknesses when dealing with complex geological area, where the uncertainties arise from the guiding model, which are input by the interpreters. In this study, we employ the Boltzmann machine, a stochastic neural network, to perform automatic pre-stack inversion for some elastic properties. Unlike the common inversion approaches, this method does not require a starting model at the beginning of the process to guide the solution; however low frequency models are required to convert the inversion-derived reflectivity terms to the absolute elastic P- and S- impedance as well as density. The process incorporates a single layer Hopfield neural network whose neurons can be treated as the desired reflectivity terms. The optimization process seeks the global minimum solution by combining the network with a stochastic model update from the Mean Field Annealing algorithm. Also, to improve the lateral continuity of the results and to stabilize the inversion process, we employ a "Z" shaped sample sorting scheme and the first order Tikhonov regularization. We applied this method to a field 2D dataset to invert for high resolution indicative P- and S-impedance sections to better capture some features away from the reservoir zone. The resulting models are strongly supported by the well results and suggested realistic features that were not displayed from the model-based deterministic inversion approach. In combination with well log analyses, we conclude those features might be potential targets for exploration purposes.



(a) **Inversion flow to obtain final log properties. The process involves two main inversion steps: (1) inverting for offset dependent reflectivity from angle gather using a convolution model, and (2) inverting for log reflectivity Rp, Rs and Rrho from offset dependent reflectivity using the linearized Zoeppritz equation from Aki and Richards (1980).**



(b) **Schematic of a Discrete Hopfield Network. This single layer network comprises of multiple neurons that are interconnected by bidirectional weighting terms W_{ij}. Once a dataset is fed into the system, the network re-organizes the responses of neurons X_i to extract some specific properties. In our inverse problem, the desired property is the reflectivity term.**



(c) **Inverted results (blue curves) plotted against the real logs (red curves) and the smooth model used to convert from reflectivity to absolute log values (cyan curves) at some well locations. Note the time scale is for reference only.**