1. Bayesian Evidential Learning 1D imaging

Uncertainty appraisal is a key concern to geophysicists when imaging the subsurface. This issue is classically handled by stochastic inversion (costly CPU) or by error propagation (unrealistic uncertainty).

Bayesian Evidential Learning 1D Imaging (BEL1D) is a Bayesian method that enables the stochastic interpretation of 1D geophysical data, with a reasonable CPU cost and realistic uncertainty estimations. The framework is based on Bayesian Evidential Learning (e.g. Scheidt et al., 2018; Hermans et al., 2016).

The method relies on the constitution of statistical relationships between model parameters and the associated data-sets from prior realizations (Fig. 1). It offers the advantage not to require the input of biased information through regularization parameters as is often the case in classical inversion processes. However, the consistent definition of a prior model space is still required. Nonetheless, the method handles efficiently large priors, the impendence being the difficulty to properly constitute representative correlations.

Above all, the method enables the quantification of uncertainty for the model parameters.

3. SNMR

Surface Nuclear Magnetic Resonance (SNMR) benefits from the quantum properties of protons (H⁺) contained in water, hence is directly sounding water in the subsurface. Current is injected/received in an antenna on the ground and interacts with the protons spins as illustrated in Fig. 3. The received signal depends on the water content (amplitude) and the way is linked to the soil particles (relaxation time).

4. Results

Prior resampling is applied to a simple 2-layers model (Fig. 4):
- As expected, we obtain a better estimation of the model parameters
- Trends in the model are discovered (increasing T₁)
- RMSE are lower

2. Iterative prior resampling

Iterative prior resampling (e.g. Cheng et al., 2019) is relatively simple and may contribute to better estimate the uncertainty. The algorithm (Fig. 2) is:

- Iteration 0: Build the initial prior model space (prior₀)
- Iteration 1: Run BEL1D with prior₀ → post₁
- Iteration 2: Run BEL1D with prior₁=post₁ → post₂
- Etc.

It enables to better constrain models since higher correlations between models parameters and data may be observed.

Prior resampling applied to BEL1D:
- Benefits from better correlation between the parameters and the data (Fig. 5)
- Enables a better estimation of the models parameters (especially in the case of large priors)
- Permits to discriminate low probability modes in posterior distribution
- The MCMC software DREAM (Vrugt, 2016) took about half an hour to converge towards an acceptable level of uncertainty whereas BEL1D needed about 3 minutes.