

Introduction

In this paper the "total space inversion" method is presented, a seismic inversion technique based on combining factual and simulated data, (see Fig. 1). The method is intended for fields with (some) well control and (3D) seismic coverage. Representative datasets are compiled in total space, which is defined as a combination of real space and model space. Real space has been sampled by factual wells and surface seismic data. Model space is sampled by simulated wells and corresponding synthetic seismic responses. Physical properties, seismic response and seismic-stratigraphy are related in the method via an integration framework. This framework is a generic description of acoustic-stratigraphic entities, grouped at three hierarchical scale levels: units, facies and lithologies, respectively. Rocktypes are assigned to lithologies, enabling the system to handle acoustic hydrocarbon effects. Each well in the system, being factual, or simulated, is constructed from framework entities. Model space is defined by attaching geological rules, probability density functions, constraints and correlations, to framework entities.

In the inversion step there are two options available for analysis of the relationship between seismic response and well properties: direct inversion and segmentation. In direct inversion, artificial neural networks, i.e. Multi-Layer Perceptrons (MLP's) or Radial Basis Functions (RBF's) networks, are trained to recognise specific well properties from the seismic response. Optionally, the data are transformed prior to analysis, e.g. seismic attributes are calculated, or a reservoir property is calculated from acoustic properties. In segmentation the seismic response is clustered. The various clusters are subsequently analysed and statistically described in terms of framework entities. Segmentation is used in cases when many non-unique solutions exist in the representative dataset.

The direct inversion approach of the "total space inversion" concept is demonstrated with a number of experiments in model space.

Experiments

Starting point is a simple model of a carbonate gas field with a homogeneous overburden. In various experiments networks are trained to estimate the net thickness of the gas column and the average density of the gas-filled reservoir rock from the seismic response. The average density is calculated as:

$$\rho = \frac{\sum_{i=1}^n \rho_i \lambda_i}{\sum_{i=1}^n \lambda_i} \quad 1$$

where:

ρ is the density, λ the layer thickness, i the layer index and n the number of layers.

In the first set of experiments, the network design, i.e. number nodes in the input and hidden layer and the type of activation function, is varied. Also different network paradigms (MLP vs RBF) are compared. After each variation, the network performance on the test data set is measured. In the second set of experiments, the network is fixed, but the geological model is made more complex by introducing new variables that affect the seismic response. In the third set of experiments the seismic bandwidth is varied.

Conclusions

The main conclusions are:

- In order to avoid extrapolation of results, the seismic time-gate to be analysed must cover the response of the largest thickness, for thickness-related inversions.
- The size of the hidden layer should not be chosen too small.
- A one node hidden layer can predict one variable only.
- One hidden layer is sufficient.
- Performance of RBF networks is worse than that of MLP networks, probably because the dimension of the problem is too large to handle for RBF networks
- The tangent hyperbolic activation function gives the best overall prediction performance.
- Prediction performance of the linear and ramp activation functions is good for the density because this is a linear problem outside the tuning range.
- The performance of the predictions of density and gas-column thickness are independent of the seismic band-width.
- With the direct inversion approach, network performance deteriorates when new variables are introduced in the model space. This affects the seismic response and target variables independently. In other words: performance deteriorates when non-unique solutions are introduced in the training set.
- When many non-unique solutions exist, segmentation of the seismic data should be used, followed by analyses of the various clusters.

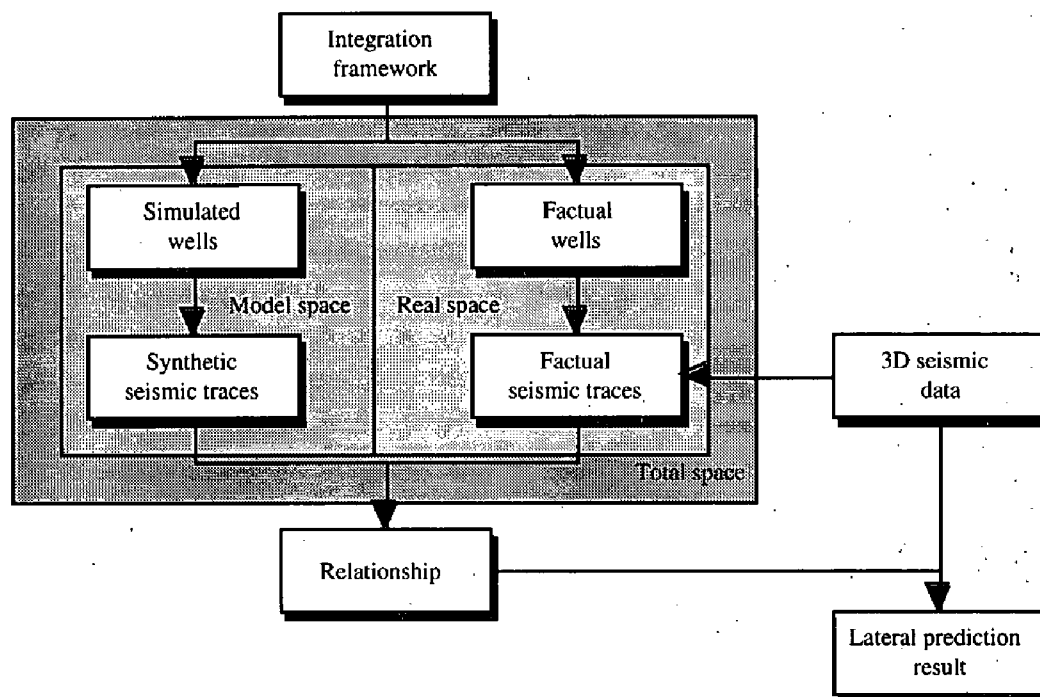


Figure 1 "Total space inversion" concept.