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A stochastic simulation of geologic intervals constrained by lithofacies proportions and stratification

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Summary

Stochastic seismic inversions have been largely applied in uncertainty assessments for the exploration of natural resources. These inversion workflows demand the generation of exhaustive realizations of lithofacies sequences that mimic plausible geologic scenarios. In this study, we present a framework that yields a direct enforcement of lithofacies proportions and stratification on the simulation of lithofacies models. This advancement was made possible by the definition of a novel metric that quantifies the stratification for vertically arranged lithofacies.

Introduction

In exploration, direct geological observations are limited to sparse wells that can be insufficient to describe the true variability in the subsurface. In this context, forward modeling of pseudo-wells has been utilized in a wide span of applications to fill data gaps with "what if" scenarios (Mavko *et al*., 2020). Stochastic approaches for pseudo-well generation have been integrated into seismic inversion algorithms and used to expand the training data for machine learning applications (Mukerji *et al*., 2001; Downton *et al*. 2020; Allo *et al*., 2021). One fundamental step in these processes is the generation of lithofacies sequences. Each outcome model holds a unique vertical arrangement of lithofacies characterized by features, such as lithofacies proportions, the number of layers, and their thicknesses. However, the current simulation methods utilize Monte Carlo/Markov Chain approaches that, typically, depend on statistics such as transition probabilities or criteria and bed thickness distributions (de Groot *et al*., 1996; Conolly and Hughes, 2016; Grant *et al*., 2019). In this study we present a stochastic simulation approach where the lithofacies proportion and the stratification can be explicitly and simultaneously enforced.

Theory / Method / Workflow

We defined a metric, hereafter called the H-index, to quantify the stratification. We assume that the simplest intercalation possible is one layer per observed lithofacies, regardless of their proportions. Thus, the H-index is a measure of deviation from that simple configuration according to a mathematical function chosen by convenience. Its formulation is versatile and defined as:

$$H = \frac{\sum_j^R f(\alpha r_j; \boldsymbol{\theta}) - \sum_i^K f(\alpha h_i; \boldsymbol{\theta})}{\sum_j^R f(0; \boldsymbol{\theta}) - \sum_i^K f(\alpha h_i; \boldsymbol{\theta})}, \quad (1)$$

where r_j are the relative thicknesses of the R layers, and h_i is the relative total thickness of each lithofacies K. The parameter α corrects for missing lithofacies in the pseudo-well, and it corresponds to the ratio between the simulated and the total number of possible lithofacies. The

function $f(x;\boldsymbol{\theta})$ can be any monotonic function where $|f(0;\boldsymbol{\theta})| \geq |f(x;\boldsymbol{\theta})|\ \forall\ x \in [0,1]$ to ensure that $H \in [0,1)$. Naturally, the interpretation of the H-index depends on the choice of $f(x)$ and its parameters $\boldsymbol{\theta}$.

Our workflow yields deterministic or stochastic enforcement of lithofacies proportions and the H-index. The next step consists of drawing a number of layers and their thicknesses for each lithofacies, respecting the intrinsic constraints imposed by the lithofacies proportions. The H-index is then calculated, and this process repeats iteratively until the H-index converges to the target value. After convergence, the layers are arranged precluding contiguous layers of the same lithofacies. Therefore, alternating layers are ensured satisfying the condition:

$$R_{i_{max}} \leq R - R_{i_{max}} + 1, \tag{2}$$

where $R_{i_{max}}$ is the maximum layer count across all lithofacies.

Results

Examples of the simulation outcomes are shown as pseudo-wells with variable lithofacies proportions and a fixed H-index of 0.800 (Figure 1). As expected, all three models exhibit similar number of layers (31, 29, and 31, respectively) and thickness distributions (typically below 100 samples, with a median of 43, 37, and 53 samples, respectively).

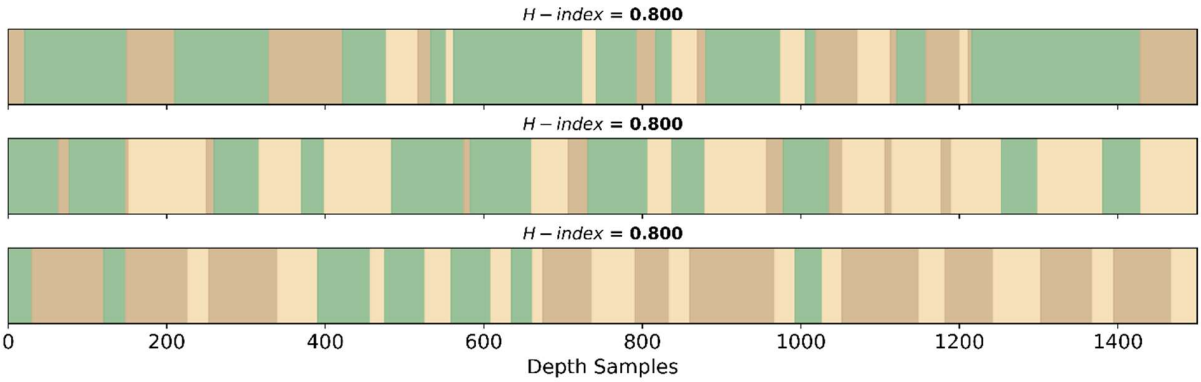


Figure 1: *Simulated pseudo-wells with variable lithofacies proportions and H-index fixed in 0.800.*

Alternatively, Figure 2 illustrates other outcomes where all have the same lithofacies proportions, but the H-index varies from 0.150 for small deviations from the most homogeneous model to 0.885 with intense stratification. These cases show a significant difference between the number of layers and thickness distributions.

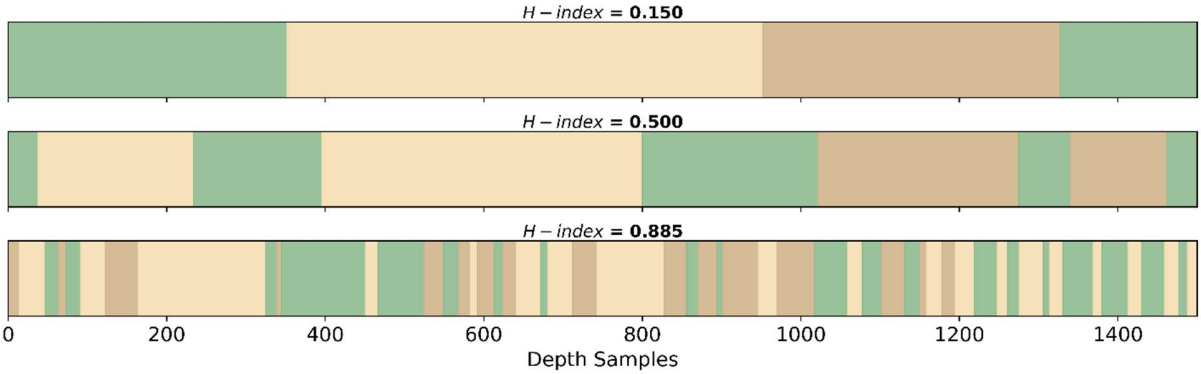


Figure 2: *Simulated pseudo-wells with lithofacies proportions fixed at 35% (green), 25% (dark yellow), and 40% (yellow) and a wide range of H-index values.*

The last example shows 1,000 outcomes of the stochastic simulation where we enforced a full range of lithofacies proportions and H-index values (

Figure 3). The ternary plot depicts the proportions among three lithofacies. Each data point corresponds to a unique lithofacies model, and the colors indicate the corresponding H-index. This result demonstrates that our simulation workflow was able to generate multiple scenarios of stratification regardless of the lithofacies proportions.

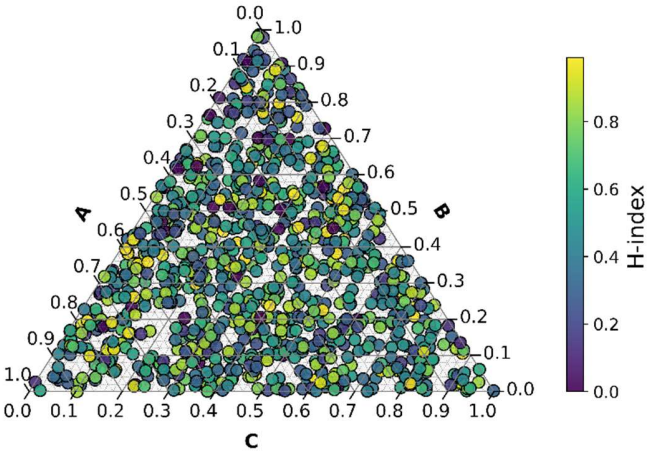


Figure 3: *Ternary plot exhibiting 1,000 data points that corresponds to the lithofacies proportions in the simulated pseudo-wells, with colors indicating the H-index. The realizations cover the whole solution space for both proportions and H-index.*

Conclusions

We have presented a stochastic framework to simulate lithofacies sequences with simultaneous control of proportions and stratification. The latter can be quantitatively described by a new metric defined here as the H-index, which has three main advantages. First, it is bounded between 0 and 1. Second, it does not depend on scale because it relies on lithofacies proportions and relative thicknesses. Finally, it is flexible to emphasize different stratification features based on the choice of a convenient mathematical function $f(x, \boldsymbol{\theta})$. This stochastic framework can be integrated into pseudo-well simulations for seismic inversion and machine learning applications.

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