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Determination of Reservoir Lithology from Seismic Data by a 2D Hidden Markov Random Field Model

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Summary

In this study, geological prior information is incorporated in the classification of reservoir lithologies using the Markov Random Field (MRF) technique. The prediction of hidden lithologies in seismic data is based on measured observations such as seismic inversion results, which are associated with the latent categorical variables derived from the distribution of Gaussian assumptions. The Hidden Markov Random Field (HMRF) approach can connect similar lithologies laterally (horizontally) while ensure a geologically reasonable stratigraphic (vertical) ordering. It is, therefore, able to exclude randomly appearing lithologies caused by errors in the inversion. In HMRF, the prior information consists of a Gibbs distribution function and transition probability matrices. The Gibbs distribution connects similar lithologies and does not need a geological definition derived from non-case-related information. The transition matrices provide preferential transitions between different lithologies and an estimation of these matrices implicitly depends on the depositional environments and juxtaposition rules between different lithologies.

Introduction

The classification of lithologies is an essential step in reservoir characterization and in the building of a static reservoir model. In most studies, a lithology classification scheme is provided by the geologists. Preliminary analysis of core and well-log data will identify various lithologies, and the number of lithologies will be kept constant afterwards. Other sources of information, such as seismic data can provide a larger 3-D coverage, adding important information and thereby overcoming the limitations provided by sparse (1-D) well locations.

Inference of lithologies from seismic data is a challenging task and actually an ill-posed inverse problem, because a variety of different lithological characteristics may result in identical or similar seismic responses (Larsen *et al.* 2006). The Bayesian concept is usually applied to mitigate this problem. Mukerji *et al.* (2001), for example, identified lithology/fluid (LF) classes based on amplitude-versus-offset (AVO) analysis, and Buland and Omre (2003) developed a linearized AVO inversion approach under the Bayesian framework.

The approach mentioned above, however, is point- or location-based, which means that the spatial coupling between data points is not considered. In order to address this problem, prior information can be included in which a Markov Chain or a Markov Random Field is applied (Eidsvik *et al*. 2004).

In this paper, first a short introduction of the Markov Random Field is given, and then the theory of the Gaussian Mixture Model based Hidden Markov Random Field (GMM-HMRF) is described. Some synthetic examples will be shown followed by a discussion and conclusion.

Markov Random Field

First introduced by Ising (Ising 1925), a Markov Random Field (MRF) is an undirected graphical model that can be described by a group of random variables that possess a Markov property. This Markov property can be defined by a joint probability distribution, which is determined by a local conditional distribution. Figure 1 illustrates this concept in which the white node is independent of all other black nodes given the red nodes.

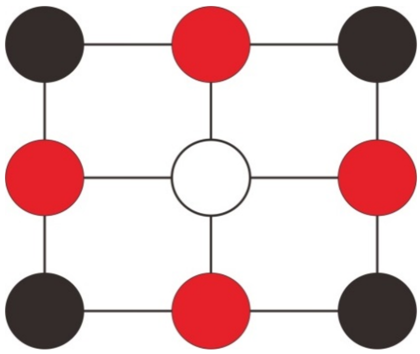

Figure 1 *Schematic view of the dependency between nodes.*

The conditional distribution of the white node can be specified as a Gibbs form:

$$\Pr(\mathbf{Z}) = \frac{1}{X} e^{-U(\mathbf{Z})} \tag{1}$$

where $\Pr(\mathbf{Z})$ is the probability distribution of random variables $\mathbf{Z}$, $U(\mathbf{Z})$ in the energy function, and X is the partition function.

Gaussian Mixture Model based Hidden Markov Random Field (GMM-HMRF)

Similar to Hidden Markov Models (HMMs) (Eidsvik *et al*. 2004), Hidden Markov Random Field (HMRF) techniques are also trying to uncover the categorical variables that are hidden to the observers (Figure 2). The difference with HMMs is that the theory of the MRF is applied, which has no limitation in 1-D (depth). That is why it is more suitable for quantifying reservoir properties in 2-D or even 3-D.

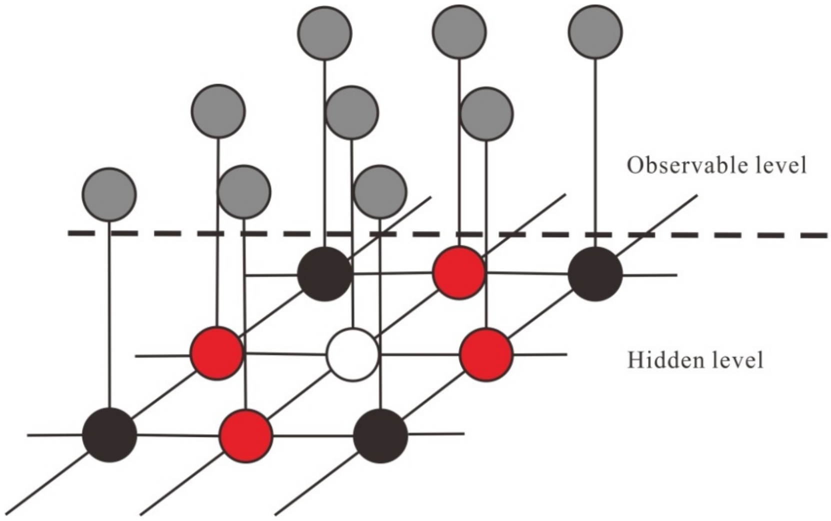

Figure 2 *Hidden Markov Random Field with observable and hidden levels.*

In HMRF, according to the Maximum A Posterior (MAP) criterion, the purpose is to seek the states $\hat{\mathbf{Z}}$ that satisfy:

$$\hat{\mathbf{Z}} = \underset{\mathbf{Z}}{\operatorname{argmax}}\{\Pr(\mathbf{Y}|\mathbf{Z},\boldsymbol{\theta})\Pr(\mathbf{Z})\} \tag{2}$$

where $\Pr(\mathbf{Z})$ is the prior probability, which is a Gibbs distribution in equation (1); $\Pr(\mathbf{Y}|\mathbf{Z},\boldsymbol{\theta})$ is the joint likelihood probability of the observation $\mathbf{Y}$.

A typical characteristic of $\Pr(\mathbf{Y}|\mathbf{Z},\boldsymbol{\theta})$ is the conditional independence (Zhang *et al*. 2001):

$$\Pr(\mathbf{Y}|\mathbf{Z},\boldsymbol{\theta}) = \prod_i \Pr(Y_i|Z_i,\theta_{Z_i}) \tag{3}$$

Then a Gaussian Mixture Model (GMM) is adopted, which is different from a single Gaussian function, to model the complexity in the distribution of the observation data ($\Pr(Y_i|Z_i,\theta_{Z_i})$. This function can be described with the following equation with parameter sets θ_j (a specified θ_{Z_i} when $Z_i = S_j$) in which there are k components:

$$\theta_j = \{(\mu_{j,1},\sigma_{j,1},\omega_{j,1}),\cdots,(\mu_{j,k},\sigma_{j,k},\omega_{j,k})\} \tag{4}$$

where $\omega_{j,k}$ is a mixture weight of the k^{th} component given a specific state S_j.

In order to account for the geological prior information, the profile Markov matrix ($P_{(:,:)}$) is introduced (Ulvmoen and Omre 2010) and equation (2) has to be formatted into equation (5) which can be solved with the Expectation-Maximization (EM) method:

$$\hat{\mathbf{Z}} = \underset{\mathbf{Z}}{\operatorname{argmax}}\{\Pr(\mathbf{Y}|\mathbf{Z},\boldsymbol{\theta})\Pr(\mathbf{Z})P_{(:,:)}\} \tag{5}$$

Book Cliffs Example

The example provided for the application of this approach is a synthetic Book Cliffs model created by Feng *et al*. (2017) in which more details have been added and more differentiation is included for the potential reservoir lithologies than in the original. As a test, only a subset of the whole 2-D section has been selected, and Figure 3 shows the true and inverted properties in terms of κ and M ($\kappa = 1/K$, with K being the bulk modulus; $M = 1/\mu$, with μ being the shear modulus).

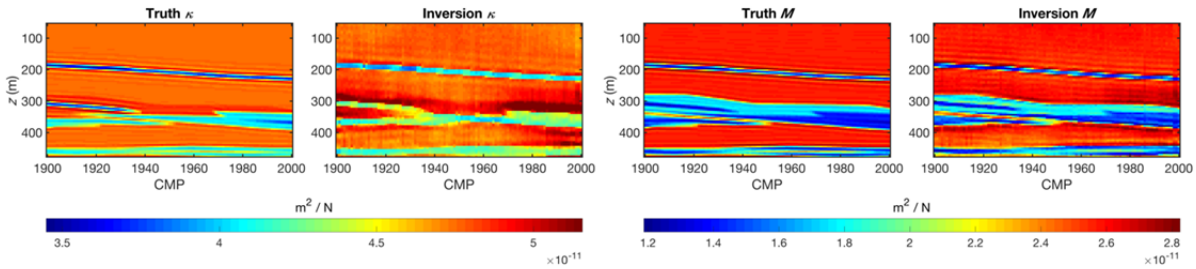

Figure 3 *True and inverted properties of a selected part from the Book Cliffs model.*

The truth is shown in Figure 4 and the starting model of the classification is in Figure 5, which is derived from a non-iterative histogram-based statistical approach with the two “drilled” wells as lithological templates and inversion results as inputs (CMPs 1900 and 2000).

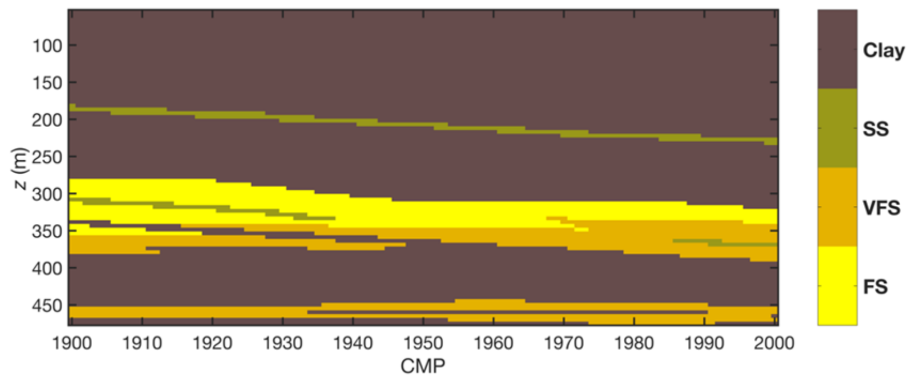

Figure 4 *Subsurface cross section in terms of lithologies (SS: Siltstone; VFS: Very fine-grained sandstone; FS: Fine-grained sandstone).*

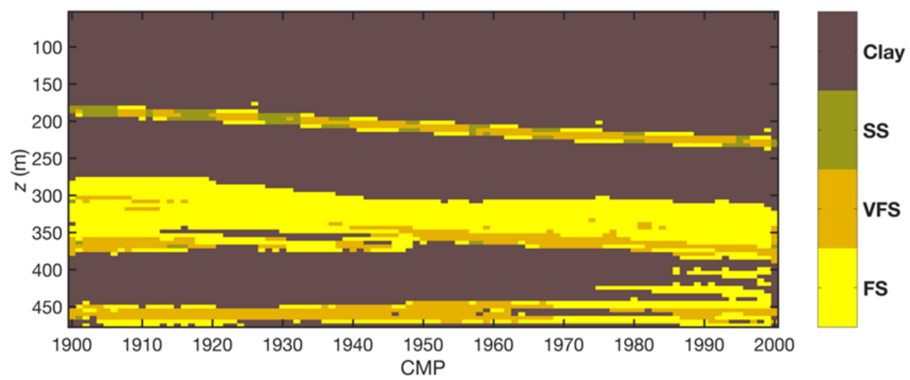

Figure 5 *Starting model in terms of lithologies.*

The final prediction of lithologies applying equation (5) is shown in Figure 6.

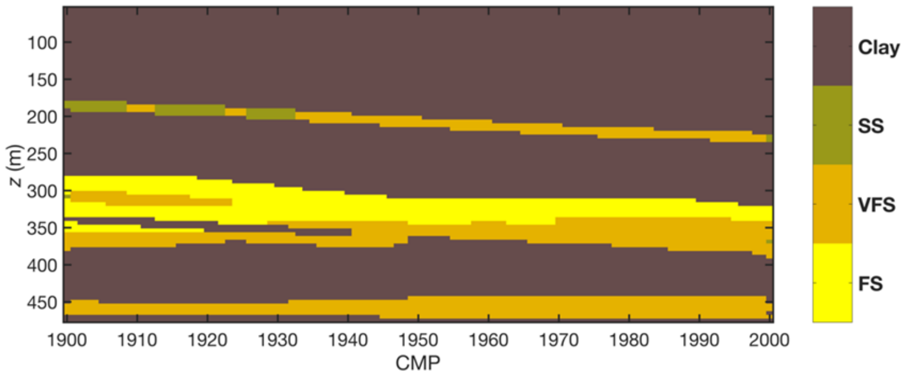

Figure 6 *Result of GMM-HMRF with the application of equation (5).*

Discussion and Conclusion

In this study, the spatial correlation during the lithological classification process is taken into account through the concept of MRF, in which the Gibbs prior and the profile Markov matrix are incorporated. In contrast to other statistical methods such as those based on histograms, which do not use the geological spatial prior knowledge, the proposed GMM-HMRF is able to produce better images of the categorized variables, and each lithology tends to connect with the same or similar lithology horizontally and vertically based on preferential transitions.

The input data for the classification are the full wave-form seismic inversion results that can provide high resolution since the nonlinear relationship between the rock properties and seismic data has been exploited by utilizing wave-mode conversions and multiple scattering. In contrast to rock properties such as bulk density and acoustic velocity, the compressibility (κ) and shear compliance (M) are used here because they appear naturally in the elastic wave-equations and are more closely related to rock types.

Acknowledgements

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