Journal of Petroleum Science and Engineering 134 (2015) 237–246

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

journal homepage: www.elsevier.com/locate/petrol

Inversion of well logs into facies accounting for spatial dependencies and convolution effects

D.V. Lindberg [a,*], E. Rimstad [b], H. Omre [a]

[a] Department of Mathematical Sciences, Norwegian University of Science and Technology, 7491 Trondheim, Norway
[b] Statoil ASA, Postboks 40, 9481 Harstad, Norway

ARTICLE INFO

Article history:
Received 1 April 2015
Received in revised form
14 September 2015
Accepted 16 September 2015
Available online 26 September 2015

Keywords:
Bayesian categorical inversion
Hidden Markov models
Deconvolution
Forward–Backward algorithm

ABSTRACT

We predict facies from wireline well log data for a fluvial deposit system offshore Norway. The wireline well logs used are sonic, gamma ray, neutron porosity, bulk density and resistivity. We solve this inverse problem in a predictive Bayesian setting, and perform the associated model parameter estimation. Spatial vertical structure of the facies is included in the model by a Markov chain assumption, making geological model interpretation possible. We also take convolution effect into account, assuming that the observed logs might be measured as a weighted sum of properties over a facies interval. We apply the methods on real well data, with thick facies layers inferred from core samples. The proposed facies classification model is compared to a naive Bayesian classifier, which does not take into account neither vertical spatial dependency, dependencies between the wireline well logs nor convolution effect. Results from a blind well indicate that facies predictions from our model are more reliable than predictions from the naive model in terms of correct facies classification and predicted layer thickness.

1. Introduction

Determination of categorical attributes like facies or lithofacies throughout a well is usually performed by qualitative well log and core sample analysis, developed from geological experience and rock physics models. This classification is of importance in exploration and development of petroleum reservoirs. Continuous wireline logs are collected in most wells and contain quantitative information, but because of noise and possible convolution they may have limited information regarding the true rock properties. Because reservoir properties are directly measured on core samples, the results are typically the most reliable petrophysical data. However, such data are only available in small numbers of cored wells for many fields since coring introduces additional cost and risk during drilling. Where available, the core plugs are usually sampled discretely throughout the well, moreover they may be preferentially sampled. In some locations along the well it may not be possible to extract core plugs resulting from fractures and poorly consolidated plugs, while other locations may be over-represented caused by easier sampling. Thus, both the geologist and the petrophysicist need to use petrophysical logs for facies recognition and well evaluation, but because of convolution effects in the logging measurement, facies recognition may be challenging and data evaluation inaccurate. An inversion of the petrophysical logs may therefore be valuable both for geologist and petrophysicist. In this paper, we study facies along a vertical 1D-profile through the subsurface layers. The objective is to create a model for prediction of the subsurface layers based on the observed wireline well logs. This is an ill-posed inverse problem, as multiple facies combinations may return the same observed well logs because of various noise components.

Several classification methods for facies and lithofacies determination from multiple logs are presented in the literature. The two main classification approaches are based on artificial intelligence and multivariate statistical methods. Artificial intelligence methods include artificial neural networks (Qi and Carr, 2006; Tang et al., 2011), and fuzzy logic (Cuddy, 2000; Chang et al., 1997). Multivariate statistical classification methods include discriminant and cluster analysis, regression analysis (Guo et al., 2007; Tang and White, 2008), statistical tree-based analysis (Perez et al., 2005), and Bayesian analysis. In this study we focus on Bayesian classifiers.

By approaching the problem in a Bayesian fashion, we are able to incorporate in the model a priori knowledge along with the information carried by the well log data. General geological knowledge, derived from geological exploration of the facies in the reservoir, is captured in the prior model. The forward function, defining the petrophysical well log measures given the facies, is specified as a likelihood model. The prior and the likelihood

* Corresponding author. Present address: DNV GL, Veritasveien 1, 1363 Høvik, Norway.
E-mail addresses: davidlin@math.ntnu.no (D.V. Lindberg), EIRIM@statoil.com (E. Rimstad), omre@math.ntnu.no (H. Omre).

http://dx.doi.org/10.1016/j.petrol.2015.09.027
0920-4105/

models define the posterior model representing the facies distribution along the well, given the observations. In Loures and Moraes (2006), porosity and clay volume is predicted in a Bayesian framework based on rock physics likelihood models, which again is used to classify facies by a simple cut-off model. In Coudert et al. (1994) and Li and Anderson-Sprecher (2006), a Bayesian classification method is described in which the well logs are assumed to be independent, the likelihood models are estimated by Gaussian distributions and the prior model is defined as the lithofacies proportions in the well. Li and Anderson-Sprecher (2006) terms this approach a naive Bayesian (NB) classifier, which is found to be superior to linear discriminant analysis, and a Gaussian likelihood model outperforms non-parametric kernel density models. A similar classifier by use of beta likelihood models is described in Tang and Ji (2006) and Tang and White (2008), and this model appears to perform better than probabilistic neural networks, linear discriminant analysis and multinomial logistic regression. Consequently, Bayesian inversion seems to be well suited for facies classification from well log data.

Most facies classification methods found in the literature assume that the well logs are vertically elementwise independent. To take spatial dependency into account the predictions are sometimes post-processed, see for example Qi and Carr (2006) in which predicted thin lithofacies layers are removed to avoid small-scale alterations. In the current study, we include spatial dependency by choosing a prior facies model according to Eidsvik et al. (2004). The underlying spatial coupling is captured with a Markov chain assumption in the prior facies model, in which each element in the well conditioned on the rest of the well is dependent on its closest neighbors only. Geological restrictions like invalid transitions between facies classes can then be incorporated in the model.

The observed well logs register a spatial convolution of the true physical properties, often termed the shoulder effect (Theys, 1999). This entails that each registration is a weighted sum of the properties in a vertical interval, the weights are sometimes referred to as the filter function (Kaaresen and Taxt, 1998). We choose to denote the weight vector as a wavelet, according to the terminology of seismic inversion with the same interpretation. The wavelets shape and width are different for each well log, and are controlled by the respective well logging tools. The tool specifications are often unknown to well log analysts, making this a deconvolution problem with unknown wavelets. The convolution models presented in this study are inspired by the work of Larsen et al. (2006) and Rimstad and Omre (2013).

2. Problem definition and field data

We consider in this case study two wells from the same geological field, a training well and a test well. The facies and well log profiles in the two wells are displayed in Fig. 1, and have been rescaled to 0.1 m intervals. In Section 3, we estimate all model parameters from the given facies and well log data in the training well. We then attempt to classify the facies profile from the well log profiles in the training well, and assess the predictive performance. Next, we apply the estimated model parameters from the training well when predicting facies in the test well.

The main interest in this study is on whether the facies predictions improve when we include in our model convolution effects in the well log profiles and spatial dependency in the facies profile. Information on the convolution effect introduced by the different logging tools is typically not given by the logging companies and is challenging to find. Both the vertical resolution and the expected shape of the convolution effect depend on both the logging speed (for statistical measurements), the sampling rate, and the tool specifications. A fictitious example displaying the convolution effect is given in Fig. 2. The well log rock properties, in convolution with the given wavelet, constitute the smoothed measured well log properties which corresponds to the well log data given in Fig. 1.

The geological system in this study is a meandering fluvial system, thus the depositional facies are dominated by processes associated with rivers or streams. These systems are heterogeneous, i.e. the reservoir properties vary between the facies and also within the facies. The facies proportions also vary from well to well as can be seen from Fig. 1. Facies is here separated into three possible classes, with properties and description given in Table 1. The facies logs in Fig. 1 are interpreted by geologist by use of view cut of the cores and well logs in cored interval and well logs only in uncored sections. Throughout the depth interval considered here, the core coverage is high.

The original wireline well logs were logged by the same logging company in the mid-1980s. The continuous logs in this study include log-sonic (LOGDT), gamma ray (GR), neutron porosity (NPHI), bulk density (RHOB) and log-resistivity (LOGRT). The

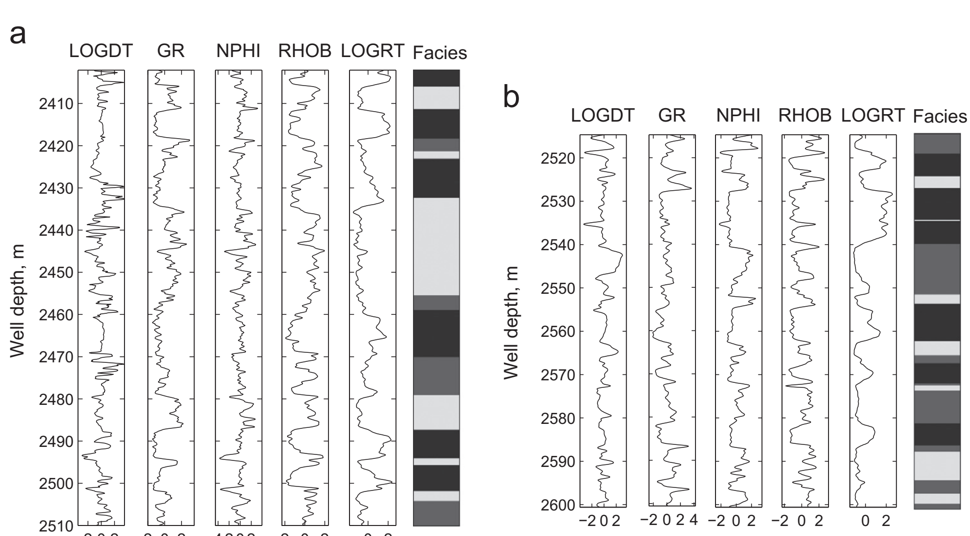

Fig. 1. Rescaled observed well logs LOGDT, GR, NPHI, RHOB, LOGRT and facies in (a) training well over a depth interval of about 2400–2510 m below the subsurface and (b) test well over a depth interval of about 2515–2600 m below the subsurface. See Table 1 for a description of the facies classes by color.