Sequential Bayesian methods for spatial on-line pore-pressure prediction from well log data

Jacopo Paglia¹, Jo Eidsvik¹, Arnt Grøver² and Ane Lothe²

¹Department of Mathematical Sciences NTNU, Norway ²Exploration and Reservoir Technology Group SINTEF Industry, Norway

20/09/2018



Jacopo Paglia, Jo Eidsvik, Arnt Grøver and Ane Lothe Sequential Bayesian methods for spatial on-line pore-pressure prediction

э



Quantify uncertainty in pore pressure prediction using data assimilation method.

Problem description



Figure: 3D grid of a subsurface domain

Workflow:

- 1 train a prior distribution from realizations of pore pressure obtained from Pressim;
- 2 specify the likelihood model for well log data based on the available logs in the vicinity of the current location;
- 3 use a sequential updating method to get online pore pressure prediction.

Prior model - geometry of data used to fit model









Prior model - pore pressure realization



Figure: Pressures

Jacopo Paglia, Jo Eidsvik, Arnt Grøver and Ane Lothe Sequential Bayesian methods for spatial on-line pore-pressure prediction

Image: A match a ma

э

Constraint:

$$p_{h_i} < p_i < p_{ob_i}.$$

Logistic transform:

$$egin{aligned} x_i &= \log\left(rac{p_i - p_{h_i}}{p_{ob_i} - p_i}
ight) \ \Rightarrow p_i &= rac{e^{x_i}p_{ob_i} + p_{h_i}}{1 + e^{x_i}}. \end{aligned}$$

Jacopo Paglia, Jo Eidsvik, Arnt Grøver and Ane Lothe Sequential Bayesian methods for spatial on-line pore-pressure prediction

()

Prior model - linear regression

For each layer of the overpressured area we fitted a linear regression model

$$x_{i_k,k} = \beta_{0,k} + \beta_{1,k} s_{i_k,k} + \epsilon_{i_k,k}$$
 $k = 6, \dots, 18$



Figure: Residuals of the regression analysis for lager 8. Example 1 and the regression analysis for lager 8.

Prior model - fit variogram



(a) Empirical semivariogram (square) and fitted exponential semivariogram (solid line) for layer 8.

(b) Empirical semivariogram (square) and fitted exponential semivariogram (solid line) for compartment 41.

$$\gamma_k(h) = \sigma_k^2 \left(1 - \exp\left(-\frac{h}{r_k}\right) \right) \quad k = 6, \dots, 18,$$

$$\gamma_c(h) = \sigma_c^2 \left(1 - \exp\left(-\frac{h}{r_c}\right) \right) \quad c = 1, \dots, 41.$$

Jacopo Paglia, Jo Eidsvik, Arnt Grøver and Ane Lothe

Sequential Bayesian methods for spatial on-line pore-pressure prediction

Prior model - prior covariance matrix

$$\boldsymbol{\Sigma}(\boldsymbol{s}_{i,k}, \boldsymbol{s}_{j,l}) = \sigma^2 \exp\left(-\frac{\sqrt{(s_{i1,k} - s_{j1,l})^2 + (s_{i2,k} - s_{j2,l})^2}}{r_1} - \frac{|s_{i3,k} - s_{j3,l}|}{r_2}\right)$$



Jacopo Paglia, Jo Eidsvik, Arnt Grøver and Ane Lothe Sequential Bayesian methods for spatial on-line pore-pressure prediction

-

Prior model - mean



Figure: Pore pressure prior mean (black) with a 90% prediction interval (green)

Image: A matrix

- - E - N

Likelihood model - well log data



Figure: Well log measurements as function of the measured depth (MD). In the likelihood fitting the black dashed parts are ignored.

Likelihood model - rock physics relation ¹

$$\mathbf{y}_{j} = \begin{pmatrix} r_{j} \\ \phi_{j} \\ \Delta t_{j} \end{pmatrix} = \begin{pmatrix} \begin{pmatrix} \frac{p_{ob_{j}} - p_{j}}{p_{ob_{j}} - p_{h_{j}}} \end{pmatrix}^{1/n_{r}} r_{0} e^{bz_{j}} \\ \phi_{0} \exp\left(-\frac{p_{ob_{j}} - p_{j}}{p_{ob_{j}} - p_{h_{j}}} c_{\phi} z_{j}\right) \\ \left(\Delta t_{ml} - \Delta t_{m}\right) \exp\left(\frac{p_{j} - p_{ob_{j}}}{p_{ob_{j}} - p_{h_{j}}} c_{t} z_{j}\right) + \Delta t_{m} \end{pmatrix} + \begin{pmatrix} \epsilon_{r_{j}} \\ \epsilon_{\phi_{j}} \\ \epsilon_{\Delta t_{j}} \end{pmatrix} \\ \Rightarrow \mathbf{y}_{j} = \mathbf{g}_{j}(p_{j}) + \epsilon_{j}, \quad \epsilon_{j} \sim N(0, \mathbf{R}), \qquad j = 1, ..., N$$

¹Zhang J. Pore pressure prediction from well logs: methods, modifications, and new approaches. Earth Sci Rev 2011; 108:50–63.

Likelihood model - paremeters values



$$\hat{\boldsymbol{R}} = \frac{\sum_{j=1}^{N} (\boldsymbol{y}_{j} - \boldsymbol{g}_{j}(\mu_{j})) (\boldsymbol{y}_{j} - \boldsymbol{g}_{j}(\mu_{i}))^{t}}{N} - \frac{\partial \boldsymbol{g}_{j}}{\partial p_{j}} \Big|_{\boldsymbol{\mu}_{j}} Var(p_{j}) \frac{\partial \boldsymbol{g}_{j}}{\partial p_{j}} \Big|_{\boldsymbol{\mu}_{j}}^{t}$$
$$\hat{\boldsymbol{R}} = \begin{pmatrix} 6.8137 & 0.1503 & 8.5835 * 10^{-5} \\ 0.1503 & 0.0083 & 4.4036 * 10^{-6} \\ 8.5835 * 10^{-5} & 4.4036 * 10^{-6} & 2.5930 * 10^{-9} \end{pmatrix}.$$

Jacopo Paglia, Jo Eidsvik, Arnt Grøver and Ane Lothe Sequential Bayesian methods for spatial on-line pore-pressure prediction,

過 ト イヨ ト イヨト

3

Likelihood model - model errors



Sequential updating

Linearize likelihood at every step, leading to the Gaussian distribution $\pi(\mathbf{x}|\mathbf{y}_1,\ldots,\mathbf{y}_j)$. The updated mean $\mathbf{m}_j = E(\mathbf{x}|\mathbf{y}_1,\ldots,\mathbf{y}_j)$ and variance $\mathbf{V}_j = Var(\mathbf{x}|\mathbf{y}_1,\ldots,\mathbf{y}_j)$ are computed recursively over the data gathering steps:

Initialization:

• Recursive updating for $j = 1, \ldots, N$:

$$\begin{aligned} S_{j} &= G_{j} V_{j-1} G_{j}^{t} + R, \\ K_{j} &= V_{j-1} G_{j}^{t} S_{j}^{-1}, \\ m_{j} &= m_{j-1} + K_{j} (y_{j} - g_{j} (m_{j-1})), \\ V_{j} &= V_{j-1} - K_{j} G_{j} V_{j-1}. \end{aligned}$$

Jacopo Paglia, Jo Eidsvik, Arnt Grøver and Ane Lothe Sequential Bayesian methods for spatial on-line pore-pressure prediction,

()

Results - updated mean and standard deviation

Results - updated mean and standard deviation



E 990

Jacopo Paglia, Jo Eidsvik, Arnt Grøver and Ane Lothe Sequential E

Sequential Bayesian methods for spatial on-line pore-pressure prediction

Sensitivity analysis - prior model

• Case I:

$$\Sigma_{new}(s_{i,k}, s_{j,l}) = \sigma_{new}^2 \exp\left(-\frac{\sqrt{(s_{i1,k}-s_{j1,l})^2 + (s_{i2,k}-s_{j2,l})^2}}{r_1} - \frac{|s_{i3,k}-s_{j3,l}|}{r_2}\right),$$
with $\sigma_{new}^2 = 2 * \sigma^2$

• Case II:
$$\mathbf{\Sigma}_{new} = \mathbf{\Sigma} + z \mathbf{\Sigma}_{\boldsymbol{eta}_{gl}} z^T$$

• Case III: faults control lateral fluid flow.

SD values				
		143 m	0 m	
Base case	Average SD	1.16	0.97	
	SD at well site	1.47	0.93	
Case I	Average SD	2.31	1.44	
	SD at well site	2.28	1.37	
Case II	Average SD	1.50	0.98	
	SD at well site	1.48	0.95	
Case III	Average SD	4.40	1.74	
	SD at well site	4.39	1.65	

• Case IV:
$$\boldsymbol{R}_{new} = 4 * \boldsymbol{R}$$

• Case V: $R_{new} = \frac{1}{4} * R$.

SD values					
		$143 \mathrm{~m}$	0 m		
Case IV	Average SD	1.52	1.24		
	SD at well site	1.51	1.22		
Case V	Average SD	1.31	0.69		
	SD at well site	1.27	0.65		

Jacopo Paglia, Jo Eidsvik, Arnt Grøver and Ane Lothe Sequential Bayesian methods for spatial on-line pore-pressure prediction

Sensitivity analysis - data types

- Case VI: only resistivity
- Case VII: only porosity
- Case VIII: only sonic transit time
- Case IX: porosity and sonic transit time.

SD values					
		143 m	0 m		
Case VI	Average SD	1.75	1.76		
	SD at well site	1.75	1.76		
Case VII	Average SD	1.70	1.45		
	SD at well site	1.70	1.44		
Case VIII	Average SD	1.75	1.75		
	SD at well site	1.75	1.75		
Case IX	Average SD	1.57	1.10		
	SD at well site	1.56	1.05		

The main contribution of the study is pore pressure prediction highlighting the following points:

- **Bayesian modeling**: The approach provides consistent integration of pre-drill a priori knowledge about the pore pressure and the well log measurements.
- **Online**: The prediction of pore pressure is updated when the new well log data is available.
- **Spatial prediction**: The prediction is not only done near the borehole location, but also ahead of the bit and at other lateral and depth locations.
- **Uncertainty**: The spatial predictions of pore pressure are represented by a mean value best prediction and a variance/covariance description.

The work is carried out as a part of the KPN project 255418/E30: "Reduced uncertainty in overpressures and drilling window prediction ahead of the bit (PressureAhead)" and is funded by the Norwegian Research Council and the DrillWell Centre (AkerBP, Wintershall, ConocoPhillips and Statoil). ConocoPhillips have contributed with input data.

PSI - sensitivity analysis on mud weight window

