Determination of reservoir thickness and distribution using improved rescaled cokriging

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Summary

The characteristics of lithologic reservoirs, such as complex channels with lateral variations and variable thicknesses, make such reservoir features difficult to identify when using conventional geostatistical methods or applying seismic attribute methods. To decrease the uncertainty and improve the definition of the predicted map over such features, we present an improved cokriging system which combines well logs and multiple attributes directly, instead of using a data fusion method. The improved technique is applied to predict a distribution and thickness map of a channel system. The results demonstrate that our improved cokriging system can enhance the lateral resolution of the channel and reduce the uncertainty of prediction due to the use of more seismic attributes than traditionally used.

Introduction

Lithologic reservoir characterization using a combination of well log and seismic data has improved as advanced techniques of seismic exploration and analysis are developed. Several approaches have been proposed to discriminate the features of lithologic reservoirs. These methods can be sorted into two classes: geostatistical methods and seismic inversion. The former methods, such as kriging and cokriging provide an optimum fit at the wells themselves, where kriging uses only the well samples and cokriging uses both the well samples and a secondary seismic attribute. Ishii and Suzuki (1989) predicted ground thickness from a probabilistic model created by kriging, and then calculated the error distribution for soil properties. Analogously, clay thickness prediction using kriging with sampled values was implemented by Saffur (2003). Also, Yahaya (2014) discriminated sand thickness using ordinary kriging and discussed the effects of using different variograms. However, ambiguous lateral changes often result from kriging due to using only the well data, which generally undersamples the prospective area. To improve the lateral distribution, cokriging was developed by introducing a secondary variable and was applied to predict porosity by considering one seismic attribute as the secondary variable (Doyen, 1988, Doyen et al., 1996). A limitation of traditional cokriging is that it only allows one secondary attribute to be incorporated. This restricts the effectiveness of the method as more information about the reservoir properties could be obtained from the multiple seismic attributes that are frequently available.

Seismic attributes and elastic parameters can be utilized as distinct indicators with which to discriminate the properties of lithologic reservoirs. For instance, inverted elastic parameters and the AVO gradient and intercept often reveal the fluid content of the reservoir (Castagna and Smith, 1994, Li and Chen, 2008). Elastic impedance and V_P/V_S ratio extracted from prestack inversion are good indicators for identifying the thickness and lithology of the reservoir (Connolly, 1999, Duffaut et al., 2000, Dumitrescu and Lines, 2006). Acoustic impedance and amplitude from poststack seismic data will also highlight the gas/oil potential of a reservoir, and can also be implemented to estimate the sand thickness (Marfurt and Kirlin, 2001).

The uncertainty in the prediction of the reservoir will be higher with the limitation of only one applied seismic attribute. To account for this, several approaches have been suggested, in which one super-dataset is generated by combining or fusing several different attributes. This can be done with methods such as weighted average, principal component analysis, wavelet analysis and multi-attribute analysis (Guerrero et al., 1996, Russell et al., 2002, Liu et al., 2014). However, these super-datasets were created using assumptions that overlook the influence of spatial distribution patterns.

In this paper, we present an improved cokriging system involving more than one secondary variable. In other words, more than one seismic attribute or elastic parameter can be introduced into the cokriging approach. Three criteria should be considered in attribute selection for improved cokriging: 1) they should be well-correlated with expected goals i.e., the properties of the reservoir derived from well logs; 2) they should be sensitive to reservoir properties and represent different lithologies; 3) they should be independent or weakly dependent. As a review of the improved cokriging approach, the technique is applied to estimate the thickness and distribution of a lithologic reservoir.

Theory

In this section, by modifying the derivation of ordinary cokriging (Isaaks and Srivastava, 1989), we demonstrate how to derive an improved cokriging system involving more than one secondary variable. By considering the unique variation in magnitude of the seismic attributes, rescaled ordinary cokriging (ROCK) will reduce the uncertainty of extremum to some extent. Also, one single constraint for the cokriging weights may decrease the risk of arriving at unacceptable negative concentrations and enhance the role of secondary information (Goovaerts, 1998).

For these reasons, taking the improved ROCK method involving two secondary variables as an example, the estimator $\hat{u}_0$ of the improved ROCK method with two secondary variables at location 0 is defined as,

$$\hat{u}_0 = \sum_{i=1}^{n} a_i u_i + \sum_{j=1}^{m} b_j (v_j - \tilde{m}_v + \tilde{m}_u) + \sum_{k=1}^{p} c_k (x_k - \tilde{m}_x + \tilde{m}_u) \qquad (1)$$

where a_i is the weight assigned to primary dataset u_i, b_j is the weight assigned to the first secondary data v_j, c_k is the weight assigned to second secondary x_k, and $\tilde{m}_u$, $\tilde{m}_v$ and $\tilde{m}_x$ are means of primary, first secondary, and second secondary variables, respectively.

One single constraint for weights can be achieved for the estimator in Eq. 1, which can be expressed as,

$$\sum_{i=1}^{n} a_i + \sum_{j=1}^{m} b_j + \sum_{k=1}^{p} c_k = 1 \qquad (2)$$

Then, the error of estimation $\mathbf{R}$ can be calculated and its matrix notation is written:

$$\mathbf{R} = \hat{u}_0 - u_0 = \mathbf{w^t Z} \qquad (3)$$

where

$$\mathbf{w^t} = (a_1, a_2, \ldots, a_n, b_1, b_2, \ldots, b_m, c_1, c_2, \ldots, c_p, -1)$$

$$\begin{aligned} \mathbf{Z^t} = (&u_1, \ldots, u_n, v_1 - \tilde{m}_v + \tilde{m}_u, \ldots, v_m - \tilde{m}_v + \tilde{m}_u, \\ &x_1 - \tilde{m}_x + \tilde{m}_u, \ldots, x_p - \tilde{m}_x + \tilde{m}_u, u_{\mathbf{0}}) \end{aligned}$$

Therefore, the variance of $\mathbf{R}$ can be expressed as,

$$\begin{aligned} \mathbf{Var}\{\mathbf{R}\} &= \mathbf{w^t C_z w} \\ &= \sum_{i=1}^{n}\sum_{j=1}^{n} a_i a_j C_{u_i u_j} + \sum_{i=1}^{m}\sum_{j=1}^{m} b_i b_j C_{v_i v_j} + \sum_{i=1}^{p}\sum_{j=1}^{p} c_i c_j C_{x_i x_j} \\ &+ 2\sum_{i=1}^{n}\sum_{j=1}^{m} a_i b_j C_{u_i v_j} + 2\sum_{i=1}^{n}\sum_{j=1}^{p} a_i c_j C_{u_i x_j} + 2\sum_{i=1}^{m}\sum_{j=1}^{p} b_i c_j C_{v_i x_j} \\ &- 2\sum_{i=1}^{n} a_i C_{u_i u_0} - 2\sum_{i=1}^{m} b_i C_{v_i u_0} - 2\sum_{i=1}^{p} c_i C_{x_i u_0} + C_{u_0 u_0} \end{aligned} \qquad (4)$$

where, C is the auto-covariance or cross-covariance as indicated by the subscripts. To derive the cokriging system, the Lagrange multiplier method is used to minimize the error of variance, and Eq. 4 can be rewritten as

$$\mathbf{Var}\{\mathbf{R}\} = \mathbf{w^t C_z w} + + \mu\left(\sum_{i=1}^{n} a_i + \sum_{j=1}^{m} b_j + \sum_{k=1}^{p} c_k - 1\right) \qquad (5)$$

The improved ROCK system can be derived by calculating the partial derivatives of $\mathbf{Var}\{\mathbf{R}\}$ with respect to weights a, b, c and Lagrange multiplier μ, which can be written as

$$\begin{cases} \sum_{i=1}^{n} a_i C_{u_i u_j} + \sum_{i=1}^{m} b_i C_{v_i u_j} + \sum_{i=1}^{p} c_i C_{x_i u_j} + u = C_{u_0 v_j}; \quad j = 1, \ldots, n \\ \sum_{i=1}^{n} a_i C_{u_i v_j} + \sum_{i=1}^{m} b_i C_{v_i v_j} + \sum_{i=1}^{p} c_i C_{x_i v_j} + u = C_{u_0 v_j}; \quad j = 1, \ldots, m \\ \sum_{i=1}^{n} a_i C_{u_i x_j} + \sum_{i=1}^{m} b_i C_{v_i x_j} + \sum_{i=1}^{p} c_i C_{x_i x_j} + u = C_{u_0 v_j}; \quad j = 1, \ldots, p \\ \sum_{i=1}^{n} a_i + \sum_{i=1}^{m} b_i + \sum_{i=1}^{p} c_i = 1; \end{cases} \qquad (6)$$

Analogously, the matrix form of improved ROCK containing n secondary variables under one single unbiased condition can be expressed as

$$\begin{pmatrix} C_{uu} & C_{\mathrm{H}^1 u} & \cdots & C_{\mathrm{H}^n u} & 1 \\ C_{u\mathrm{H}^1} & C_{\mathrm{H}^1\mathrm{H}^1} & \cdots & C_{\mathrm{H}^n\mathrm{H}^1} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ C_{u\mathrm{H}^n} & C_{\mathrm{H}^1\mathrm{H}^n} & \cdots & C_{\mathrm{H}^n\mathrm{H}^n} & 1 \\ 1 & 1 & \cdots & 1 & 0 \end{pmatrix} \begin{pmatrix} \alpha \\ \beta^1 \\ \vdots \\ \beta^n \\ \mu \end{pmatrix} = \begin{pmatrix} C_{u_0 u} \\ C_{u_0\mathrm{H}^1} \\ \vdots \\ C_{u_0\mathrm{H}^n} \\ 1 \end{pmatrix} \qquad (7)$$

where, u is the primary data, $\mathrm{H}^1, \cdots, \mathrm{H}^n$ are n different secondary variables, C is the auto-covariance or cross-covariance related to the subscripts. α is the weight vector on the primary data, and $\beta^1, \cdots, \beta^n$ are weight vectors on the n different secondary variables, respectively.

This improved cokriging system offers a way to integrate seismic attributes related to spatial variations between well logs and seismic data, instead of the linear data fusion method. The number of attributes selected is optional depending on the quality of seismic acquisition and processing under the aforementioned criteria.

Case study

The study area is located in northern Alberta and includes 11 drilled wells (Figure 1). The reservoir target is a bitumen-bearing formation which underlies a shale caprock and uncomformably overlies a non-reservoir clastic formation. The interface between the reservoir and the underlying clastic formation is difficult to detect in the seismic data due to the similarity of the rock properties. In this case, a window from 10 ms above the top reservoir to 10 ms below the base of the non-reservoir clastic is used to produce seismic attribute slices.

To demonstrate the improved ROCK method, two seismic attributes are extracted as the secondary datasets. One is the raw amplitude of an angle stack, which is shown in Figure 2. Also the crossplot between the angle stack amplitude and formation thickness from well logs is calculated with a correlation coefficient of 0.49 (Figure 4a). The other secondary variable selected is the V_P/V_S ratio extracted from joint PP-PS inversion in the same window (Figure 3). Its crossplot against thickness and with a correlation coefficient of 0.58 is shown in Figure 4b.

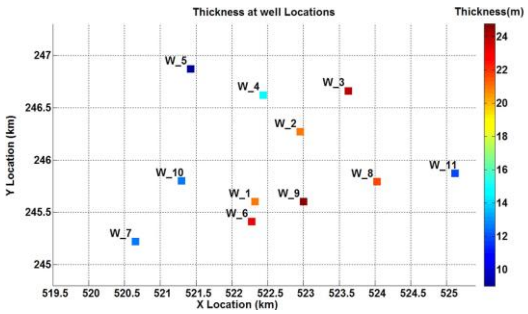

Figure 1: Well log distribution and measured reservoir thickness in the study area.

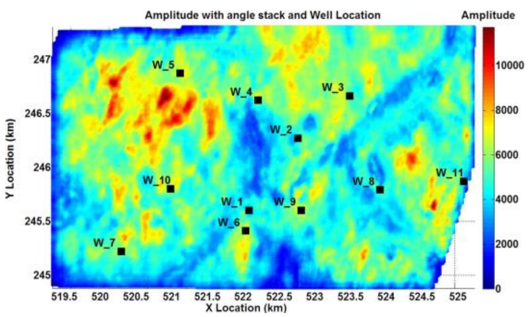

Figure 2: Seismic raw amplitude from an angle stack between 8^0 and 29^0, using a window from 10ms above the reservoir to 10ms below the base clastic formation.

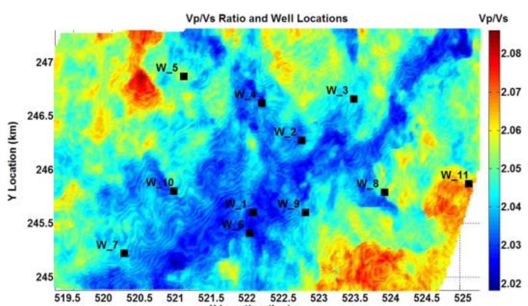

Figure 3: V_P/V_S ratio extracted from an inverted seismic volume using a window from 10ms above the top reservoir to 10ms below the base clastic formation.

Before applying the improved ROCK algorithm, the variograms of the primary and two secondary variables need to be obtained, and are shown in Figure 5. The improved ROCK method is then implemented to predict the thickness and distribution map of the reservoir (Figure 6).

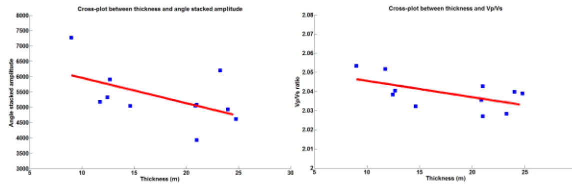

Figure 4: Crossplots between reservoir thicknesses derived from well logs and two seismic attributes. a) Crossplot between reservoir depth and angle stack amplitude, b) Crossplot between reservoir depth and V_P/V_S ratio.

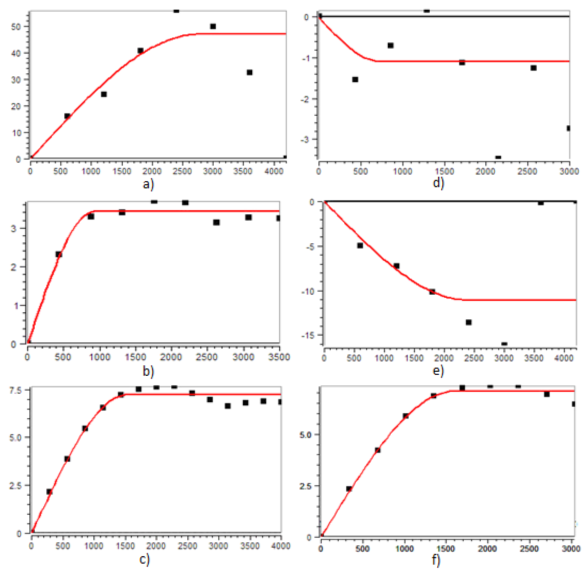

Figure 5: Variograms of the primary and two secondary variables, where a) shows the variogram of the well, b) shows the variogram of the angle stack amplitude, c) shows the variogram of the V_P/V_S ratio, d) shows the variogram of well and angle stack amplitude, e) shows the variogram of well and V_P/V_S ratio, and f) shows the variogram of angle stack amplitude and V_P/V_S ratio.

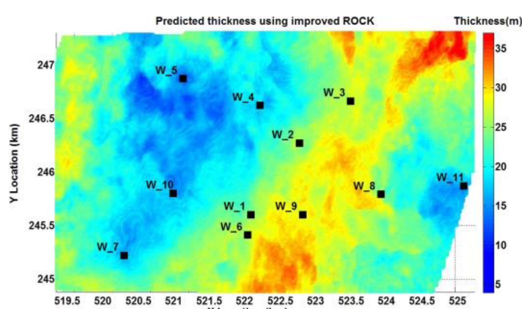

Figure 6: Predicted thickness and distribution of the reservoir formation using the improved ROCK method, obtained by considering thickness from the wells as the primary variable, and the angle stack amplitude and V_P/V_S ratio as two secondary variables.

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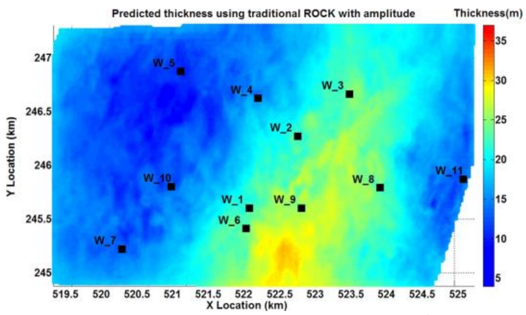

Figure 7: Predicted thickness and distribution of the reservoir formation using traditional ROCK with only one secondary variable: angle stack amplitude.

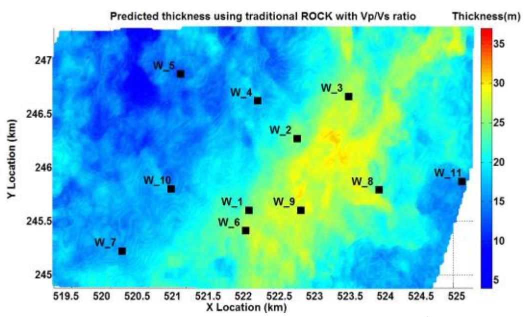

Figure 8: Predicted thickness and distribution of the reservoir formation using traditional ROCK with only one secondary variable: V_P/V_S ratio.

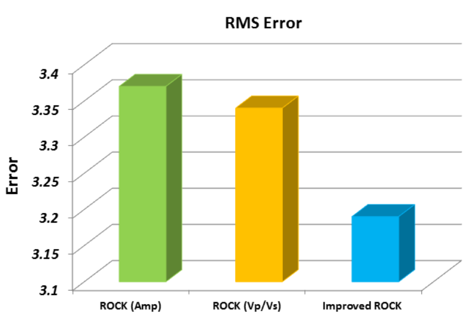

Figure 9: Root-mean-square errors using leave-one-out cross-validation for traditional ROCK with angle stack amplitude only, traditional ROCK with V_P/V_S ratio only, and the improved ROCK with these two attributes.

To examine the advantages of the predicted thickness map using the improved ROCK method, we also apply the traditional ROCK method with one secondary variable using the angle stack amplitude and V_P/V_S ratio attributes separately, with all other parameters remaining the same. The predicted thickness maps using traditional ROCK are shown in Figure 7 and 8, as related to the different attributes selected.

Leave-one-out cross-validation is then applied to quantitatively evaluate the results of the improved ROCK method. The histogram of the root-mean-square (RMS) error of the improved ROCK and traditional ROCK methods with different attributes are shown in Figure 9.

A detailed comparison of the improved and traditional ROCK methods shows that improved ROCK with multiple attributes enhances the lateral distribution of the reservoir sand prediction. The reason is that the angle stack amplitude and V_P/V_S ratios are sensitive to the reservoir properties, but they can also indicate different characteristics which ensure that more independent information is introduced. Once again, the proper selection of seismic attributes is also important for the improved cokriging and should follow the previously stated criteria.

Conclusion

Seismic attributes and elastic parameters can be used to delineate different aspects of a reservoir. In other words, the inclusion of more independent seismic attributes has the potential to better predict reservoir characteristics. We presented an improved rescaled ordinary cokriging (ROCK) system that utilizes more than one secondary variable. Our method could also be extended to other cokriging systems such as simple cokriging (SCK) and ordinary cokriging (OCK).

We implemented the improved ROCK method involving two seismic attributes and used this method to predict the thickness and distribution of a reservoir from northern Alberta. The estimated thickness map shows that the improved ROCK approach not only increased the accuracy of prediction, but also enhanced the lateral distribution in a reasonable way. A statistical analysis of this approach allows us to conclude that our proposed cokriging system has produced an improved lithological prediction of the reservoir.

Acknowledgements

We would like to thank Jian Sun for helpful discussions and innovative suggestions, and Darren Schmidt and Michael Pacholek for their assistance. We also wish to thank Murphy Oil Company Ltd for the permission to use the dataset.