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Initial model selection for efficient history matching of channel reservoirs using Ensemble Smoother

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ABSTRACT

Ensemble Smoother (ES) is one of popular reservoir characterization methods in petroleum engineering. It updates unknown reservoir parameters by integrating available data and utilizing multiple number of models, known as ensemble. In addition, ES is much faster than Ensemble Kalman filter (EnKF) due to one global update. However, ensemble-based methods have two key assumptions: Sufficient number of ensemble members is needed and the mean of the ensemble should be the best estimate among the realizations. Therefore, for reliable characterization using EnKF or ES, there should be enough number of well-designed initial models, reflecting true reservoir properties.

The objective of this study is to reduce number of ensemble members but preserve prediction quality at the same time. We use principal component analysis (PCA) for managing high dimensional data. Total 400 ensemble members are projected on 2 dimension (2D) principal component plane and separated into 10 clusters by K-means clustering. Production histories of 10 candidate models, one from each cluster, are compared to the observed data to find out the best model for the reference. As a result, good initial ensemble models can be selected near the best model on the plane and they are used in ES.

We check impacts of the sampling method in channel reservoirs by comparing 400 ensemble members with 200, 100, 50, 20, and 10 models sampled. In consideration of both time and prediction quality, around 100 are desirable numbers for uncertainty quantification and history matching. The cases with 50, 20 and 10 ensemble members may show wrong results for channel reservoirs, since EnKF and ES require more models for reliability in spite of the sampling effect.

Moreover, it has been commented that ES is vulnerable to overshooting and filter divergence problem due to its global update. By selecting well-designed initial ensemble members, however, we can get better production forecasts using ES over EnKF while total simulation time is reduced about 93%. We confirm that the proposed method is effective even in the case with uncertain reservoir information and a field-scale model, PUNQ-S3. ES with the PCA-assisted model selection enables efficient history matching with a small number of ensemble realizations and one assimilation only.

1. Introduction

Reliable forecast on reservoir performances is essential to make a reasonable decision in oil industry. However, it is challenging to figure out reservoir properties reliably. One solution is to estimate prediction uncertainty in a stochastic way by using multiple models. It helps to quantify uncertainty ranges of the reservoir properties. For uncertainty assessment, it is desirable to maintain an adequate level of uncertainties: Too wide range of uncertainty does not help our decision makings and too narrow one may lead to wrong forecast.

Reservoir models are generated by two types of data available. One is information on reservoir parameters such as permeability, porosity, and other rock properties. These are static data obtained from various sources such as coring or well logging. The other is production related information, which can be obtained after productions of oil, water, and gas. Integration of production data helps to calibrate reservoir parameters and enhance prediction quality by reducing uncertainties. Therefore, it is recommended to integrate these data available for dependable history matching.

Ensemble Kalman filter (EnKF) is one of useful data assimilation methods for uncertainty quantification and history matching. It was proposed to solve non-linear problems by Evensen (1994), following Kalman filter which was only applicable to linear dynamic system (Kalman, 1960). EnKF was first applied to oceanography and Nævdal

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Nomenclature

C	error covariance matrix
d	observation data
H	measurement operator matrix
K	Kalman gain
m	model variables
N_e	number of ensemble members
N_t	number of time steps
y	ensemble members

Superscript

a	assimilated
d	dynamic
p	priori
s	static

Subscript

i	ensemble members
t	simulation time steps

et al. (2002) used EnKF in petroleum engineering for the first time to characterize reservoir permeability.

EnKF assimilates reservoir parameters repeatedly using observed data in a real time. It is useful for combining with various algorithms and computing parallel processing with different models. These multiple models, known as ensemble, are utilized to quantify uncertainties of reservoir performances. Although EnKF has many advantages for history matching, it needs several assimilations with many ensemble models of over hundreds. Therefore, critical issues on EnKF are about time and reliability in current research.

Van Leeuwen and Evensen (1996) proposed Ensemble Smoother (ES), which assimilates reservoir parameters only once. All are same with EnKF except that the ensemble models are globally updated, using all observed data available. ES is faster but sometimes gives undesirable results compared to EnKF. In other words, it is vulnerable to overshooting and filter divergence problem. Therefore, it is challenging to use ES in non-linear problems (Skjervheim et al., 2011; Chen and Oliver, 2012, 2014; Emerick and Reynolds, 2013; Lee et al., 2013, 2014, 2016). To overcome this limitation, Lee et al. (2013) applied several Kalman gains in ES, improving characterization quality on synthetic channel fields. Lee et al., (2014, 2016) also utilized different observation data depending on water breakthroughs of each well to improve ES.

Many researchers have suggested ensemble-based methods, combined with various optimization methods. Iterative procedures were applied to improve their prediction qualities with EnKF (Gu and Oliver, 2007; Li and Reynolds, 2009) and ES (Chen and Oliver, 2012; Emerick and Reynolds, 2013). Jeong et al. (2010) proposed gradual deformation method with EnKF to minimize its objective function. Jung and Choe (2012) used streamlines and Yeo et al. (2014) employed drainage area for correlation function to localize covariance fields. Liao and Zhang (2015) added transform stage of state vectors in EnKF and applied to PUNQ-S3 model. Kang et al. (2016) applied singular value decomposition to covariance matrix of initial ensemble to compact its size of models for fast ES process.

EnKF will require a large number of ensemble to estimate reservoir parameters (Wen and Chen, 2005). Otherwise, overshooting or undershooting problem may happen, which has extremely high or low values after the updates. Many researchers suggest at least 100 ensemble members in EnKF for history matching, but it highly depends on geological complexity of reservoir (Arroyo-Negrete et al., 2008; Devegowda et al., 2007; Nævdal et al., 2011). In addition, initial ensemble models are important for final updated results in EnKF, which can be mathematically proven (Evensen, 2004; Aanonsen et al., 2009; Jafarpour and McLaughlin, 2009). Good initial models are highly desirable to have reservoir characteristics in a reliable manner, especially channel reservoirs. Therefore, by using well-designed initial ensemble members, which are feasible reservoir models, we can expect successful characterization with even small number of models.

In this paper, we propose a novel method to sample good initial ensemble members for efficient history matching of ES. Ensemble of realizations are selected using principal component analysis (PCA) and K-means clustering. They are filtered depending on whether they have similar geological properties with a true reservoir of interest. By using the proposed scheme with ES, we expect significant reduction of simulation time because ES has a single assimilation process and we use only reservoir models selected.

2. Methodologies

2.1. Ensemble Kalman filter and Ensemble Smoother

EnKF uses multiple models on its formula and state vectors constitute the ensemble. The state vector has three kinds of parameters: static variable $\mathbf{m_s}$, dynamic variable $\mathbf{m_d}$, and predicted variable $\mathbf{d}$ as Eq. (1).

$$\mathbf{y}_{t,\ i} = \begin{bmatrix} \mathbf{m}_t^s \\ \mathbf{m}_t^d \\ \mathbf{d}_t \end{bmatrix}_i \mathbf{i} = \mathbf{1}, \mathbf{N_e}, \quad \mathbf{t} = \mathbf{1}, \mathbf{N_t} \tag{1}$$

where, **i** and **t** denote the ensemble of realizations and the simulation time step, respectively.

Various parameters can be applied to the state vector depending on characterization purposes. Then, forward simulations are performed for each reservoir model in the forecast step. By using observed data

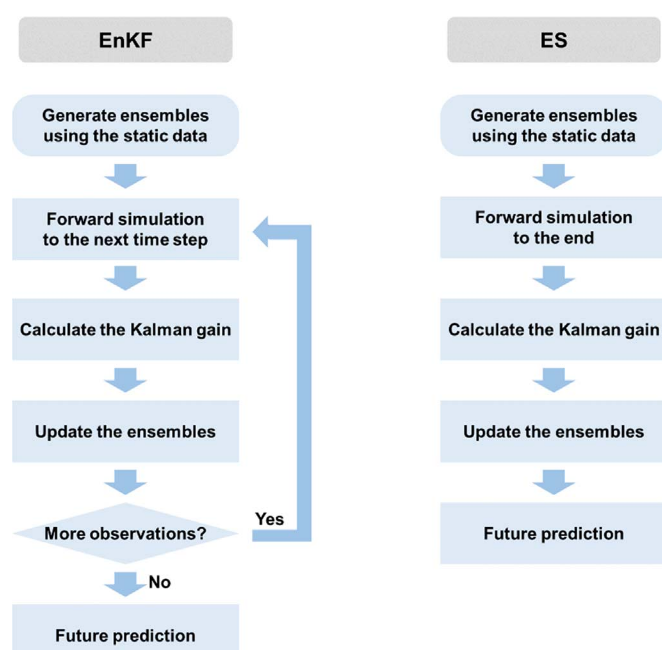

Fig. 1. Flow charts of EnKF and ES.