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Calibration of channelized subsurface flow models using nested sampling and soft probabilities

Ahmed H. Elsheikh [a,*], Vasily Demyanov [a], Reza Tavakoli [b], Mike A. Christie [a], Mary F. Wheeler [b]

[a] Institute of Petroleum Engineering, Heriot-Watt University, Edinburgh, United Kingdom
[b] Center for Subsurface Modeling (CSM), Institute for Computational Engineering and Sciences (ICES), University of Texas at Austin, TX, USA

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ABSTRACT

A new method for calibration of channelized subsurface flow models is presented. The proposed method relies on the nested sampling algorithm and on adaptive construction of soft probability maps. Nested sampling (NS) is a Bayesian sampling algorithm for estimating the Bayesian evidence and obtaining samples from the posterior distribution of the unknown fields. NS utilizes a set of samples (active set) that evolves to high-likelihood regions. The sample evolution process is achieved by iteratively replacing the sample with the lowest likelihood within the active set by a new sample from the prior but with higher likelihood value (constrained sampling). For channelized models, drawing samples from the prior model based on a training image and only accepting the samples satisfying the likelihood constraint is computationally inefficient due to low acceptance rates. We develop an efficient constrained sampling step utilizing soft probability maps in addition to the training image (using the Tau model) to obtain samples from the prior satisfying the likelihood constraint. The soft probability map is constructed by averaging the samples within the active set and is shown to significantly increase the acceptance rate of the nested sampling algorithm. The proposed algorithm is applied for calibration of several channelized subsurface flow models. In addition, the NS algorithm is applied for prior model selection of a channelized model with different training images obtained by changing the orientation angles of a reference training image. The results show that selecting the prior model based on the data mismatch can be misleading. This highlights the need to evaluate the Bayesian evidence (estimated by the nested sampling algorithm) as a more reliable prior model selection statistics, especially when the amount of calibration data is limited.

1. Introduction

Subsurface flow models rely on many parameters that cannot be measured directly. The complete distributions of these model parameters are commonly inferred by a model calibration process that takes into account the historical records of the input–output of the model. During model calibration process, the parameters are adjusted to minimize the difference between the model output from the measured time dependent data. Automated calibration is essential for accurate prediction of groundwater flow models to understand the fate of subsurface contaminants [1,2]. The multiphase flow of hydrocarbons in an oil reservoir is another example, where model calibration is needed for accurate predictions and for maximizing recovery [3]. Different parameter estimation techniques can be applied to tackle this problem. These techniques can be classified into Bayesian methods based on Markov chain Monte Carlo (MCMC) methods [4–6], gradient based optimization methods [1,2], stochastic search algorithms [7–10] and ensemble Kalman filter methods [3,11,12]. Other accelerated calibration techniques relies on replacing the full simulator by a surrogate [13], however the curse of dimensionality limits the applicability of these methods to problems with few stochastic dimensions. Some of the standard inversion techniques are readily available in the form of open source packages [14].

Calibration of subsurface reservoirs with spatial facies distribution commonly relies on multipoint statistics (MPS) [15]. First, a training image (TI) which is believed to represent the spatial phenomenon under consideration is selected. Then, a set of realizations with similar features is generated using the single normal Equation simulation (SNESIM) algorithm [15] or filter-based simulation (FILTERSIM) algorithm, [16]. Following that, these realizations are conditioned to time dependent historical input–output

* Corresponding author at: Institute of Petroleum Engineering, Heriot-Watt University, Edinburgh, EH14 1AS Scotland, United Kingdom.

E-mail addresses: ahmed.elsheikh@pet.hw.ac.uk (A.H. Elsheikh), Vasily.Demyanov@pet.hw.ac.uk (V. Demyanov), tavakoli@ices.utexas.edu (R. Tavakoli), Mike.Christie@pet.hw.ac.uk (M.A. Christie), mfw@ices.utexas.edu (M.F. Wheeler).

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response of the reservoir under consideration. However, the amount of available data to constrain the models is usually limited in both quantity and quality. This results in an ill-posed inverse problem that might admit many different solutions. In the context of calibration of channelized models, Caers and Hoffman [17] proposed the probability perturbation method (PPM) as an iterative technique for calibration of subsurface flow models with MPS features. At each iteration, the current sample is perturbed to produce a new sample that better fits the calibration data. The degree of perturbation is controlled by a single parameter that

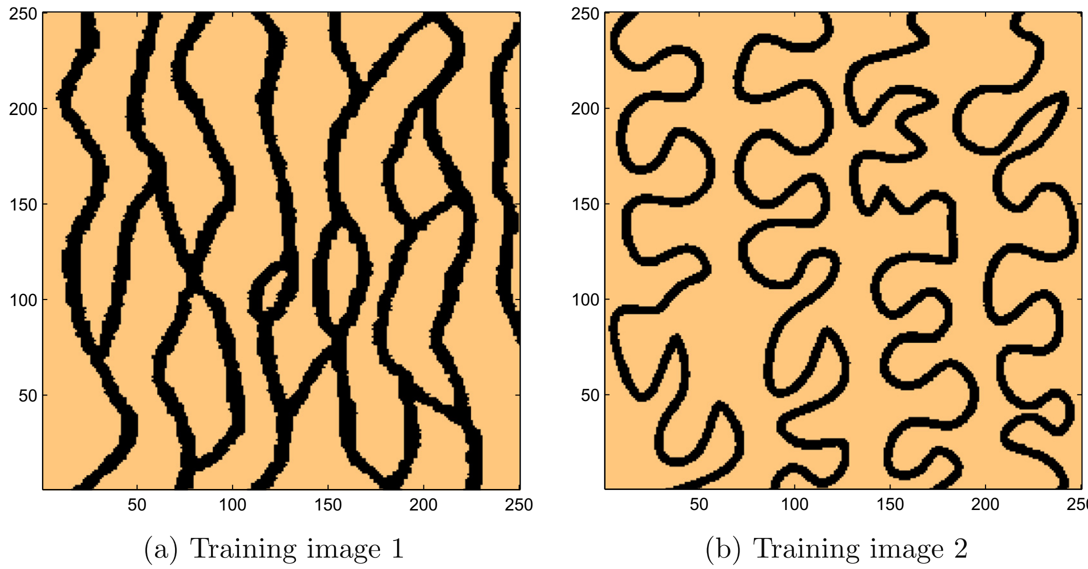

Fig. 1. Training images (TI) utilized for generating prior realizations in the different examples.

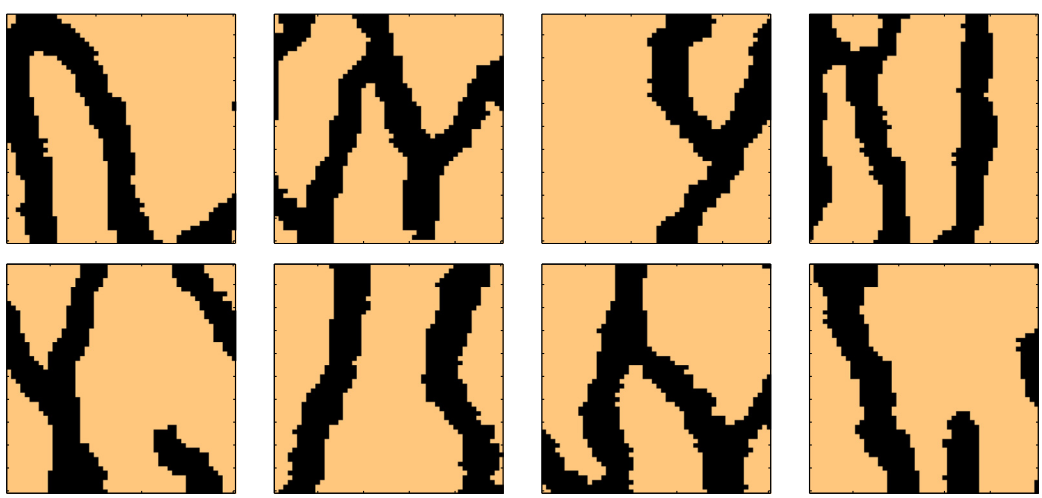

Fig. 2. Different realizations of the unconditioned permeability field obtained by the SNESIM algorithm as implemented in the SGeMS library [33].

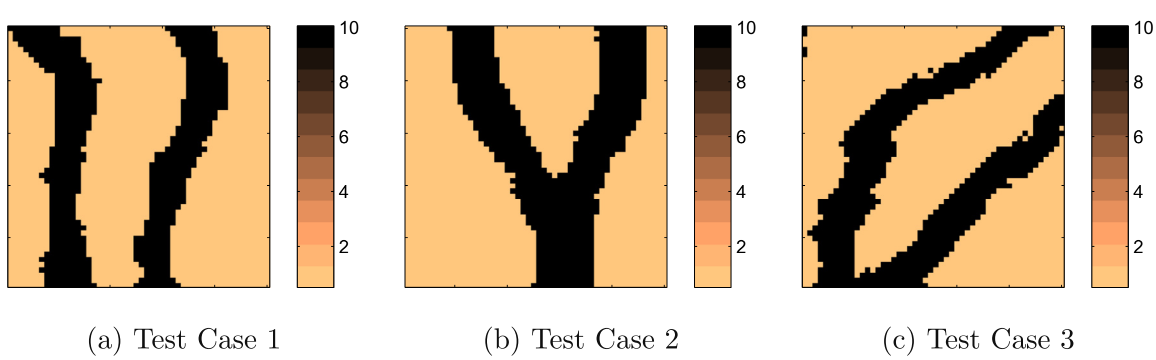

Fig. 3. Reference permeability field for test case 1, 2 and 3.