Different parameterizations of the initial ensemble for a channelized reservoir in an Assisted History Matching context

Bogdan Sebacher, Andreas Stordal, Remus Hanea

Delft University of Technology &IRIS & Statoil

22-06-2016

International Research Institute of Stavanger

Outline

The problem in hand

- Channelized reservoir estimation using the iterative adaptive Gaussian mixture filter (IAGM, Stordal et al.2014).
- A parameterization of the facies field (channelized field) is need it.
- The generation of the facies fields is performed using a multiple point geostatistical simulation (MPS) method (SNESIM) with a reliable training image.

Training image

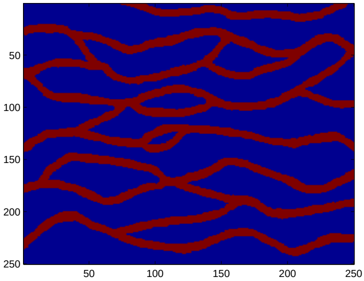


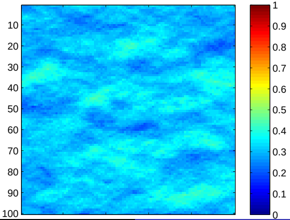
Figure : The training image

The goal

- We present a comparison between three parameterizations based on a bridge between the truncated plurigaussian simulation model (TGS) and MPS.
- The parameterization consist of defining of some random fields, marginally Gaussian, of which truncation with reliable thresholds simulate the same facies fields with those, previously obtained, from the training image with the MPS method.

Initialization

- Using MPS and the training image generate an ensemble of n_e channelized reservoirs (We present the case of a square domain with 100×100 cells)
- Calculate, from the ensemble, the probability field of the channel. For each grid cell j of the reservoir domain we have a value denoted $p^j \in [0, 1]$

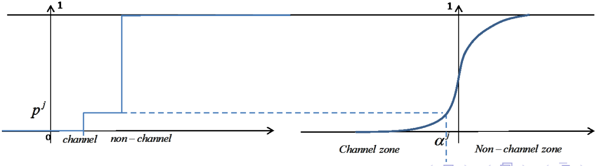


Normal score transform

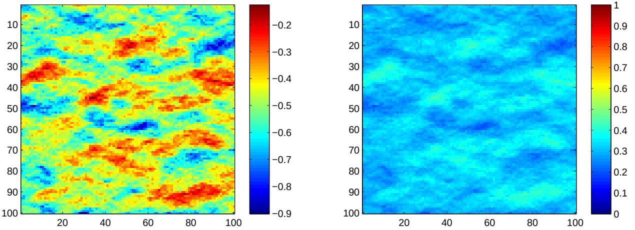
- For each grid cell j of the reservoir domain we consider the distribution:

$$facies\_distribution^j \sim \begin{pmatrix} Channel & Non-channel \\ p^j & 1-p^j \end{pmatrix} \quad (1)$$

- We link this distribution with a standard Gaussian distribution through the normal score transform



Threshold field



Concept

- We perform the parameterization of the facies fields in the normalized space.
- For each ensemble member i we have to define a numerical field θ_i by sampling from a standard normal distribution.
- Consider a grid cell j and if at this position is channel then we have to sample from $(X|X \leq \alpha^j)$ and if it is non-channel we sample from $(X|X > \alpha^j)$, where X is a standard Gaussian random variable.

Older parameterization

1. **Gravity Centers (GS)** For the member i and cell j we define (Sebacher et al. 2015):

$$\theta_i^j = \begin{cases} \mathbf{E}(X|X \leq \alpha^j) = \frac{-\phi(\alpha^j)}{\Phi(\alpha^j)} & \text{if } j \in \text{channel}, \\ \mathbf{E}(X|X > \alpha^j) = \frac{\phi(\alpha^j)}{1-\Phi(\alpha^j)} & \text{if } j \in \text{non-channel}, \end{cases} \quad (2)$$

where X is a standard Gaussian variable, $\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$ and $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{u^2}{2}} du$.

Stochastic forcing (I)

The sampling from conditional distributions could be made following at least two ideas

1. Sampling randomly for each grid cell and for each ensemble member.
2. Sampling randomly between the ensemble members but keeping the dependence structure inherited from the training image within each member.

We introduce a stochastic forcing consisting of a random seed in order to sample from the conditional distributions.

Stochastic forcing (II)

We connect the conditional distribution with uniform distributions by the means of the cumulative distribution functions:

$$\mathbf{cdf}_{X|X\leq\alpha^j}(x) = \begin{cases} \frac{\Phi(x)}{\Phi(\alpha^j)} & \text{if } x \leq \alpha^j, \\ 0 & \text{if } x > \alpha^j, \end{cases} \tag{3}$$

$$\mathbf{cdf}_{X|X>\alpha^j}(x) = \begin{cases} 0 & \text{if } x \leq \alpha^j, \\ \frac{\Phi(x)-\Phi(\alpha^j)}{1-\Phi(\alpha^j)} & \text{if } x > \alpha^j, \end{cases} \tag{4}$$

Stochastic forcing (III)

If y is a sample from the $U(0,1)$ then solving the equations:

1. $\mathbf{cdf}_{X|X\leq\alpha^j}(x) = y$, $x = \Phi^{-1}(y * \Phi(\alpha^j))$
2. $\mathbf{cdf}_{X|X>\alpha^j}(x) = y$, $x = \Phi^{-1}(\Phi(\alpha^j) + y * (1 - \Phi(\alpha^j))$

we obtain samples from the conditional distributions $(X|X \leq \alpha^j)$ and $(X|X > \alpha^j)$.

New parameterizations

For the member i and cell j we define:

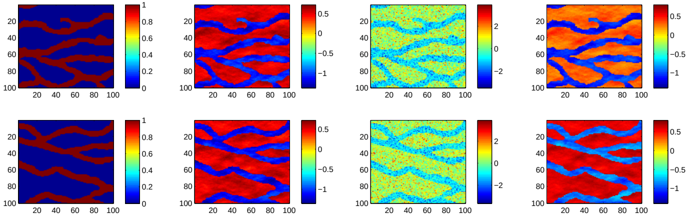
1. **Random seeds (RS)**

$$\theta_i^j = \begin{cases} \Phi^{-1}(y_i^j * \Phi(\alpha^j)) & \text{if } j \in \text{channel}, \\ \Phi^{-1}(\Phi(\alpha^j) + y_i^j * (1 - \Phi(\alpha^j)) & \text{if } j \in \text{non-channel}, \end{cases} \tag{5}$$

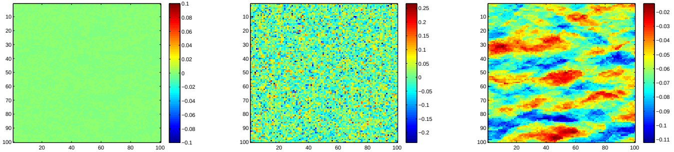
2. **Fixed seeds (FS)**

$$\theta_i^j = \begin{cases} \Phi^{-1}(y_i * \Phi(\alpha^j)) & \text{if } j \in \text{channel}, \\ \Phi^{-1}(\Phi(\alpha^j) + y_i * (1 - \Phi(\alpha^j)) & \text{if } j \in \text{non-channel}, \end{cases} \tag{6}$$

Example

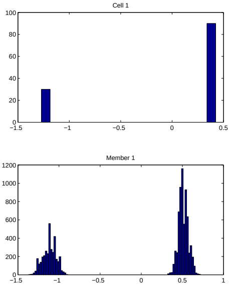


Mean fields

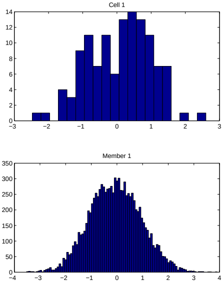


(a) GC (b) RS (c) FS

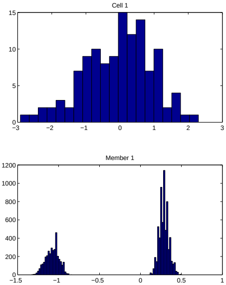
Histograms



(d) Gravity center



(e) Random seed



(f) Fixed seed

The state vector

The state vector for the ensemble member i at the assimilation time step t is

$$Z_t^i = [\theta_i^T \quad d_{sim}(\theta_i)]^T, \; i = 1, \ldots, n_e. \tag{7}$$

where $d_{sim}(\theta_i)$ are the simulated observations given the parameters and consist of the simulated production data (oil and water rates, bottom hole pressures).

AGM update

If P_t is the sample covariance matrix of $\{Z_t^i\}_{i=1}^N$ calculated based on the weighted ensemble mean:

$$\overline{Z_t} = \sum_{i=1}^{N_e} W_t^i Z_t^i \tag{8}$$

At each assimilation time, the augmented state vector is updated in the AGM for each $i = 1, \ldots, N_e$ as

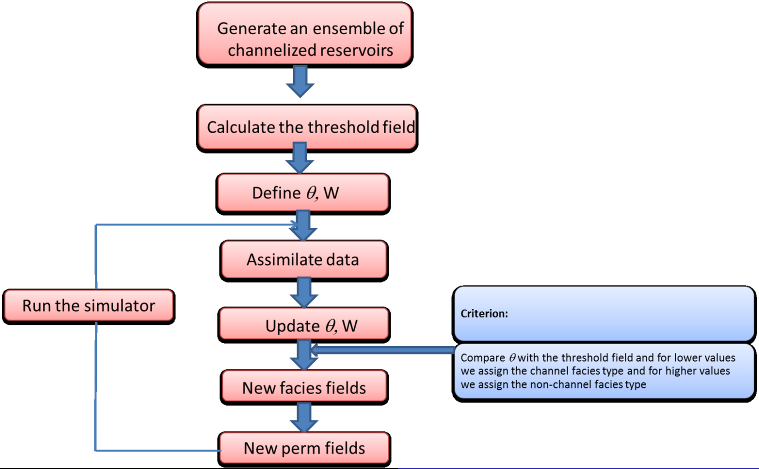
$$\hat{Z}_t^i = Z_t^i + P_t H_t^T (H_t P_t H_t^T + h^{-2} R)^{-1} \left(y_t - H_t Z_t^i + \epsilon_t^i \right) \tag{9}$$

where $h \in [0, 1]$.

AGM weights

- Initialization $W_t^i = 1/N_e$
- Update $W_t^i = \alpha_t \overline{W}_t^i + (1-\alpha_t)N^{-1}$, where
    - $\overline{W}_t^i = \frac{\hat{W}_t^i}{\sum_j \hat{W}_t^j}$
    - $\hat{W}_t^i = \Phi(y_t - H_t X_t^{f,i}, h^2 H_t P_t^f H_t^T + R) W_{t-1}^i$, where $\Phi(x-\mu, P)$ is a multivariate Gaussian distribution with mean μ and covariance P
    - $\alpha_t = N^{-1}\hat{N}_{eff} = (N\sum_{j=1}^{N}(\overline{W}_t^j)^2)^{-1}$

AGM work flow



Re-sampling

- From each updated ensemble member we obtain a facies realisation, but it may suffers from the lack of channel continuity (are not geologically plausible).
- In order to re-establish the continuity, using SNESIM and the training image, we can generate a new ensemble of facies realisation conditioned to the updated probability fields of the channel and non-channel.
- Issue: The re-sampled ensemble suffers from the data match point of view.

Iterative AGM

- The IAGM is the iterative version of the AGM where after an assimilation cycle a new initial ensemble is generated by sampling from the Gaussian mixture defined by the particles at the end of previous iteration.
- Here we re-sample from the training image with the new probability fields obtained as the weighted mean of the ensemble members after the last iteration.

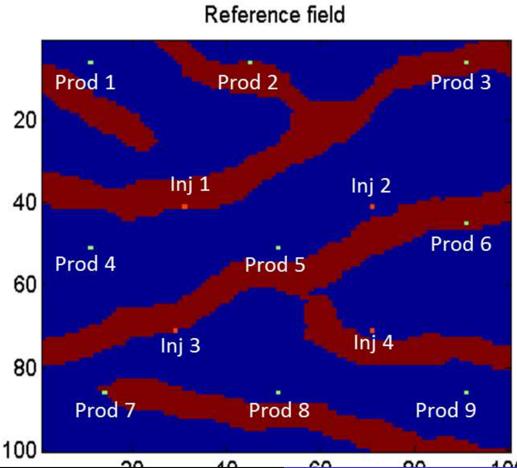
$$p_k(j) = \sum_{i=1}^{n_e} W^i Ind_k^i(j), \quad k = channel, non - channel \quad (10)$$

, for each grid cell j

Stoping criterion

- We stop when the updated ensemble of channelized reservoirs are geologically plausible.
- From our experience after two, three or maximum four iterations, but it depends on the complexity of the problem.

Reference field



Reservoir set up

- 13-spot water flooding 2D-reservoir, black oil model with 100×100 active grid cells.

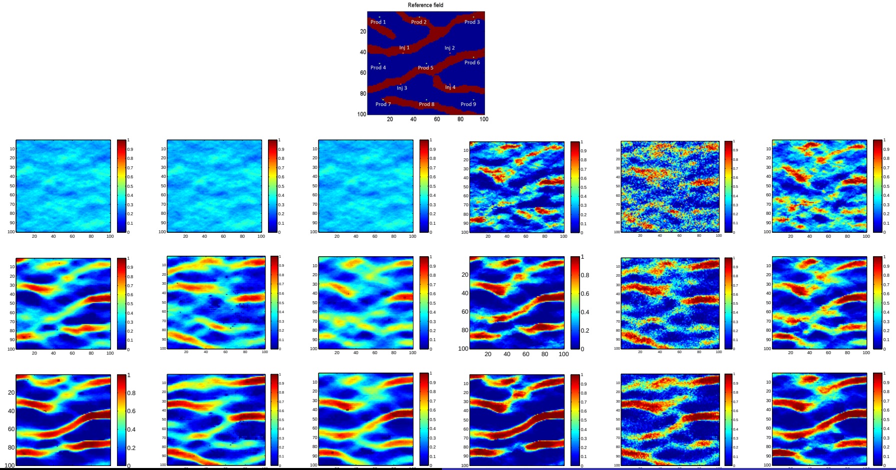
Table : The petro-physical properties

Facies type	Permeability	Porosity
Channel	9 md	0.2
Non-channel	1 md	0.2

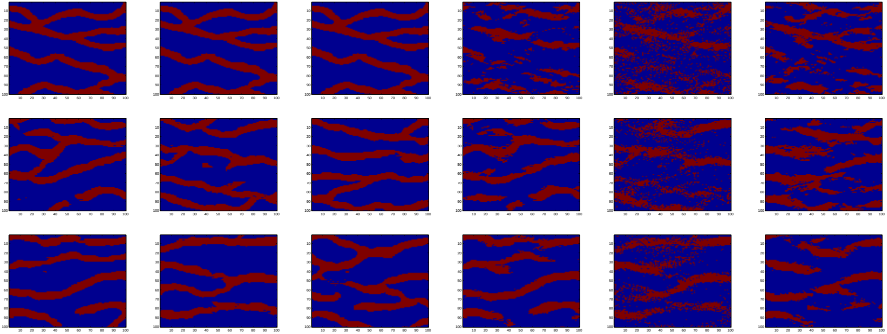
AGM and IAGM set up

1. h=0.25
2. 6 assimilation time steps of 60 days
3. The measurement errors: Gaussian with 0 mean and standard deviation of 3%
4. 3 iterations

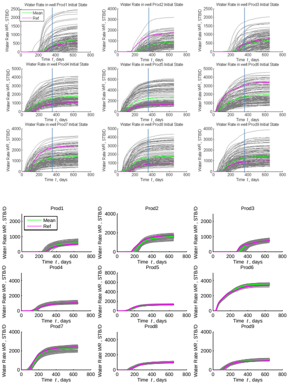
Probability fields

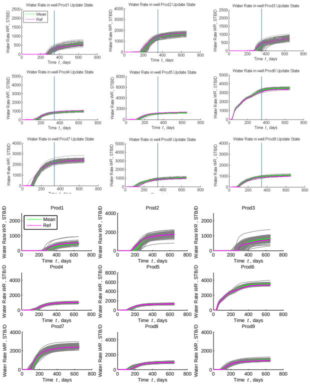


Members



Data match


Water Rate in well Prod1 Initial State
Water Rate in well Prod2 Initial State
Water Rate in well Prod3 Initial State
Water Rate in well Prod4 Initial State
Water Rate in well Prod5 Initial State
Water Rate in well Prod6 Initial State
Water Rate in well Prod7 Initial State
Water Rate in well Prod8 Initial State
Water Rate in well Prod9 Initial State
Mean
Ref
Prod1
Prod2
Prod3
Prod4
Prod5
Prod6
Prod7
Prod8
Prod9
Time t, days
Water Rate WR, STB/D


Water Rate in well Prod1 Update State
Water Rate in well Prod2 Update State
Water Rate in well Prod3 Update State
Water Rate in well Prod4 Update State
Water Rate in well Prod5 Update State
Water Rate in well Prod6 Update State
Water Rate in well Prod7 Update State
Water Rate in well Prod8 Update State
Water Rate in well Prod9 Update State
Mean
Ref
Prod1
Prod2
Prod3
Prod4
Prod5
Prod6
Prod7
Prod8
Prod9
Time t, days
Water Rate WR, STB/D

RMSE for permeability

	Gravity center		Random seed		Fixed seed	
	Initial	Updated	Initial	Updated	Initial	Updated
Iteration 1	5.201	4.781	5.201	5.059	5.201	5.059
Iteration 2	4.745	4.444	4.982	4.794	4.984	4.655
Iteration 3	4.475	4.283	4.794	4.566	4.614	4.371

RMSE for total rates

	Gravity center		Random seed		Fixed seed	
	Initial	Updated	Initial	Updated	Initial	Updated
Iteration 1	1147.3	204.16	1147.3	267.44	1147.3	192.76
Iteration 2	410.51	151.58	512.52	154.30	488.68	152.22
Iteration 3	287.05	131.25	446.25	142.07	364.32	139.52

- We presented a comparison between three parameterizations of channelized reservoirs generated with a MPS model, before and after they are coupled with a history matching method.
- Two of parameterizations were newly introduced, based on extensions of a older parameterization, involving a stochastic forcing that increases the variability within initial ensemble.

- The results show that the dependence spatial structure is important in keeping the geological plausibility during iterations while the channel distribution into the fields was equally well estimated by all parameterizations.
- The stochastic forcing used controlled seems to not improve the channel estimation and the data match and predictions, showing the same trend as the older parameterization.
- All of these proves the robustness of the parameterizations that account for the spatial dependence structure inherited from the training image.