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Parameter estimation with an iterative version of the adaptive Gaussian mixture filter

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The adaptive Gaussian mixture filter (AGM) was introduced in Stordal et. al. (ECMOR 2010) as a robust filter technique for large scale applications and an alternative to the well known ensemble Kalman filter (EnKF).
It consists of two analysis steps, one linear update and one weighting/resampling step. The bias of AGM is determined by two parameters, one adaptive weight parameter (forcing the weights to be more uniform to avoid filter collapse) and one pre-determined bandwidth parameter which decides the size of the linear update.
It has been shown that if the adaptive parameter approaches one and the bandwidth parameter decrease with increasing sample size, the filter can achieve asymptotic optimality.
For large scale applications with a limited sample size the filter solution may be far from optimal as the adaptive parameter gets close to zero depending on how well the samples from the prior distribution match the data. The bandwidth parameter must often be selected significantly different from zero in order to make large enough linear updates to match the data, at the expense of bias in the estimates.

In the iterative AGM we take advantage of the fact that the history matching problem is usually estimation of parameters and initial conditions. If the prior distribution of initial conditions and parameters is close to the posterior distribution, it is possible to match the historical data with a small bandwidth parameter and an adaptive weight parameter that gets close to one. Hence the bias of the filter solution is small. In order to obtain this scenario we iteratively run the AGM throughout the data history with a very small bandwidth to create a new prior distribution from the updated samples after each iteration. After a few iterations, nearly all samples from the previous iteration match the data and the above scenario is achieved. A simple toy problem shows that it is possible to reconstruct the true posterior distribution using the iterative version of the AGM. Then a 2D synthetic reservoir (Stordal et. al. ECMOR 2010) is revisited to demonstrate the potential of the new method on large scale problems