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On an iterative ensemble smoother and its application to a reservoir facies estimation problem

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For data assimilation problems there are different ways in utilizing the available observations. While certain data assimilation algorithms, for instance, the ensemble Kalman filter (EnKF, see, for examples, Aanonsen et al., 2009; Evensen, 2006) assimilate the observations sequentially in time, other data assimilation algorithms may instead collect the observations at different time instants and assimilate them simultaneously. In general such algorithms can be classified as smoothers. In this aspect, the ensemble smoother (ES, see, for example, Evensen and van Leeuwen, 2000) can be considered as an smoother counterpart of the EnKF.

The EnKF has been widely used for reservoir data assimilation (history matching) problems since its introduction to the community of petroleum engineering (Nævdal et al., 2002). The applications of the ES to reservoir data assimilation problems are also investigated recently (see, for example, Skjervheim and Evensen, 2011). Compared to the EnKF, the ES has certain technical advantages, including, for instance, avoiding the restarts associated with each update step in the EnKF and also having fewer variables to update, which may result in a significant reduction in simulation time, while providing similar assimilation results to those obtained by the EnKF (Skjervheim and Evensen, 2011).

To further improve the performance of the ES, some iterative ensemble smoothers are suggested in the literature, in which the iterations are carried out in the forms of certain iterative optimization algorithms, e.g., the Gaussian-Newton (Chen and Oliver, 2012) or the Levenberg-Marquardt method (Chen and Oliver, 2013; Emerick and Reynolds, 2012), or in the context of adaptive Gaussian mixture (AGM, see Stordal and Lorentzen, 2013). In Emerick and Reynolds (2012) the iteration formula is derived based on the idea that, for linear observations, the final results of the iterative ES should be equal to the estimate of the EnKF. In Chen and Oliver (2013), the iteration formula is obtained based on the standard Levenberg-Marquardt (LM) algorithm. By discarding certain model terms in the standard LM algorithm, an approximate iteration formula, similar to those in Emerick and Reynolds (2012); Stordal and Lorentzen (2013), is derived.

In this contribution we show that the iteration formulae used in Chen and Oliver (2013); Emerick and Reynolds (2012) can also be derived from the regularized Levenberg-Marquardt (RLM) algorithm in inverse problems theory (Engl et al., 2000), with certain linearization approximations introduced to the RLM. This not only leads to an alternative theoretical tool in understanding and analyzing the behaviour of the aforementioned iterative ES, but also provides insights and guidelines for further developments of the iterative ES algorithm. As an example, we show that an alternative implementation of the iterative ES can be derived based on the RLM algorithm. For illustration, we apply this alternative algorithm to a facies estimation problem previously investigated in Lorentzen et al. (2012), and compare its performance to that of the (approximate) iterative ES used in Chen and Oliver (2013).

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