Implicitly localized MCMC sampler to cope with nonlocal/nonlinear data constraints in large-size inverse problems

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Many practical applications involve the resolution of large-size inverse problems, without providing more than a moderate-size sample to describe the prior probability distribution. In this situation, additional information must be supplied to augment the effective dimension of the available sample, for instance using a covariance localization approach. In this study, it is suggested that covariance localization can be efficiently applied to an approximate variant of the Metropolis/Hastings algorithm, by modulating the ensemble members by the large-scale patterns of other members. Modulation is used to design a (global) proposal probability distribution (i) that can be sampled at a very low cost, (ii) that automatically accounts for a localized prior covariance, and (iii) that leads to an efficient sampler for the augmented prior probability distribution or for the posterior probability distribution. The resulting algorithm is applied to an academic example, illustrating (i) the effectiveness of covariance localization, (ii) the ability of the method to deal with nonlocal/nonlinear observation operators and non-Gaussian observation errors, (iii) the reliability, resolution and optimality of the updated ensemble, using probabilistic scores appropriate to a non-Gaussian posterior distribution, and (iv) the scalability of the algorithm as a function of the size of the problem. The codes are openly available from github.com/brankart/ensdam.