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Interactive Comment

Interactive comment on "DREAM$_{(\mathrm{D})}$: an adaptive markov chain monte carlo simulation algorithm to solve discrete, noncontinuous, posterior parameter estimation problems" *by* J. A. Vrugt

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1 General assessment

The paper by Jasper Vrugt is following a long series of papers on this topic of DREAM (DiffeRential Evolution Adaptive Metropolis) algorithms developed by the author, from 2003 onwards. The major idea of the DREAM algorithms seems to be the use of several sequences in parallel (or of a population of points) in an MCMC setting. This reminds me of works in the 1990's by Laird Breyer and Gareth Roberts, on coupled

MCMC. Assuming an artificial target that is the product of the original targets, MCMC schemes that move the whole population at each iteration conditional on the previous population obviously allows for a sort of adaptivity, in the sense that empirical moments can be derived from this population. However, since the target increases in dimension, the drawback is that convergence clearly takes longer than with a single chain, despite the adaptive features. The current paper is more specifically an adaptation of the general DREAM scheme for a discrete state space, with the only change being to consider the integer part of the original DREAM random-walk perturbation. However, the new algorithm contains an unclear step (b) referring to the "crossover probability" that I do not understand: CPR is not defined, there is at least one typo (the second z_j^i should be x_j^i) and the fact that d' keeps decreasing by a factor 1 is not possible in the long run, so important detail is missing. As a consequence, I also do not understand why this does not impact detailed balance. This needs to be clarified.

Overall, I am thus unconvinced by the claims made in the paper as to the perfect adequation of the new DREAM algorithm to the discrete optimisation problem, in the sense that there is very little in the design of this new DREAM that takes the problem into account: DREAM(D) is a mere discretisation of DREAM and the scale of the moves is dictated by the variability of the population at the previous step, assuming a sort of connexity that is less common in discrete state spaces. In the sudoku example used in the paper, the values in a given entry of the sudoku grid have no ordinal meaning in the sense that 7 is just as far from 8 than 1. A discrete space distance (and the resulting divergence between populations) would thus seem more appropriate than a linear distance (and the resulting scale) in this case.

2 The examples

The first example found in the paper is a sudoku solver, a problem I personally find quite interesting although unrelated with HESS. Important details such as the construction of the likelihood are missing from the paper. Although the goal is to maximise the likelihood (which then provides the unique solution to the sudoku), the paper seems to advocate a regular MCMC dynamic, with time-homogeneous Markov kernel and target density. It thus seems that the global optimum is hit by chance along the way.

The second example is about an hydrology complex model (hence connected with HESS) whose description is missing (the reference to Figure 3 is inadequate since this is a sudoku related graph). It appears as a somehow contrived problem if the quote "Each parameter is discretized equidistantly in 250 intervals with respective step size listed in the last column at the right hand side. This gridding is necessary to create a non-continuous, discrete, parameter estimation problem" is to be taken into account. The conclusion of this section is that the new DREAM algorithm applied to the discretised version of the problem is doing as well as the original DREAM algorithm applied to the original model. There is no optimisation in this case.

I thus feel the paper is missing a more convincing hydrology example that would produce an optimum in a truly discrete state space.

3 About adaptivity

Overall, I strongly object to the use of the adjective "adaptive" both in the name of the algorithm and in the title, next to MCMC, because this method is not an "adaptive MCMC" algorithm in the sense of Andrieu, Haario, Roberts, Rosenthal, and others, in that the Markov kernel on the product space does not change along iterations. There is no need for convergence to occur beyond detailed balance (Figure 2 being rather un-

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helpful in that respect). Therefore the references to strictly adaptive MCMC algorithms are not relevant. (Note that the title is missing upper case letters for Markov, Monte and Carlo.)

4 Conclusion

I am not convinced at this stage the paper is appropriate for the HESS journal. The new method is a valid addition to the collection of DREAM algorithms developed by the author and the co-authors, however the relevance of using this specific algorithm to conduct discrete optimisation is not demonstrated by the current version. For instance, using a time-homogeneous Markov chain for optimisation, as opposed to the time-heterogeneous original Metropolis et al. (1953) simulated annealing approach, sounds too naïve for large discrete spaces.

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