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Implicit Particle Filters: a Numerical Case Study Using the Lorenz Attractor

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There are many problems in science, for example in meteorology, oceanography and geomagnetism, in which the state of a system must be identified from an uncertain model supplemented by noisy data. The goal is to assimilate the data by merging the observations with the model. Data assimilation problems are typically formulated in a Bayesian framework: given a set observations $\{b^n\}$ taken at times $t_n \leq t$, one forms the conditional probability for the state $x(t)$ of the model given $\{b^n\}$, i. e. one estimates $P\left(x(t)|\{b^n\}\right)$. The state estimate is a functional (usually the mean) of P. Particle filters are simulation based sequential Monte Carlo (SMC) methods for nonlinear, non-Gaussian data assimilation in which a weighted ensemble of N particles (replicas of the model) with positions x_i and weights w_i approximates P by $\sum_{i=1}^{N} \delta(x(t) - x_i)w_i$. Traditional particle filters first generate positions using a known transition density (the prior) and weight the particles using the observations. The catch is that most weighting schemes generate positions with low weights, and consequentially the number of particles required can be very large. The implicit particle filter is a SMC method that finds high probability positions by using the available observations from the outset so that they are in the high probability region, reducing sharply the number of particles needed.

We demonstrate the effectiveness of the implicit particle filter by performing numerical experiments with a Lorenz attractor driven by white noise, a popular testbed for data assimilation algorithms. We apply and compare two recent implementations of the implicit filter and contrast them with standard SMC techniques. We discretize Lorenz's equations using (*i*) the Euler scheme, and (*ii*) the Klauder-Petersen scheme (a second-order, stochastic, Runge-Kutta like scheme), so as to address the question of how the dynamics of the continuous time model affect the performance of discrete filters. The assimilation of sparsely available data into the Lorenz attractor is a hard problem for most filters, especially if the gap between observations is large; the implicit particle filter performs very well on this problem and is able to reconstruct synthetic data with fewer particles and larger time gaps than competing filters. We also show success with the assimilation of spatially sparse observations (e.g. observing only one of the three variables) and with nonlinear observation operators. These results bode well for application of implicit particle filters to more demanding problems with more variables.