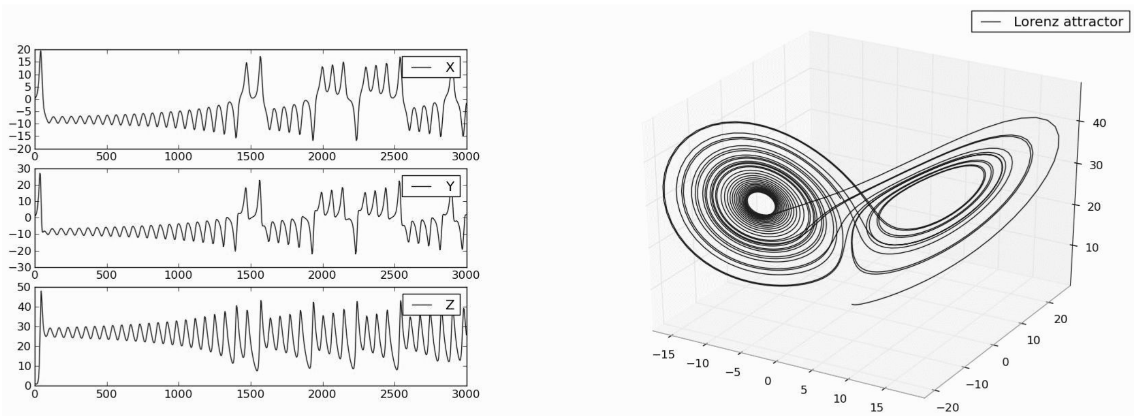
A Hybrid Filtering Methodology for Nonlinear Estimation

[1]Hofman Radek, [2]Dedecius Kamil

We are concerned with Bayesian estimation of a discrete stochastic process governed by a nonlinear model. We employ marginalized particle filter (MPF, [5])—which is also known as Rao-Blackwellised particle filter, [2]—for on-line tuning of nuisance parameters of analytical filters.

Particle filtering [1] is a general filtering methodology applicable to nonlinear and non-Gaussian systems. However, intensive sampling is in high-dimensional spaces computationally prohibitive. MPF arises when the structure of the model allows marginalization over a subset of state variables [5]. Selected state variables are then estimated with an analytical filter and the rest is treated using particle filter. The marginalization substantially reduces the dimension of the space we sample from. This is of particular significance in high-dimensional estimation problems emerging, e.g., in geoscientific applications.

The methodology is demonstrated on estimation of a three-dimensional chaotic nonlinear system given by the Lorenz attractor [4]. We use the extended Kalman filter (EKF, [3]) for estimation of the three coordinates of the attractor and the particle filter for adaptive tuning of model error covariance in EKF. EKF is the nonlinear version of the Kalman filter [6]. It uses linearized version of a nonlinear differentiable state transition function to propagate posterior covariance matrix. Jacobian of the Lorenz attractor is approximated at each time step using forward differences. Observations are simulated by the attractor, which is integrated forward with the fourth-order Runge-Kutta scheme, and perturbed with a Gaussian noise. Satisfactory accuracy of estimation was achieved even with a small number of particles.



References

[1] A. Doucet, N. De Freitas and N. Gordon. *Sequential Monte Carlo methods in practice.* Springer Verlag, 2001.

[2] A. Doucet, N. De Freitas, K. Murphy and S. Russell. *Rao-Blackwellised particle filtering for dynamic Bayesian networks. Proceedings of the Sixteenth Conference on Uncertainty in Artificial Intelligence*, 176–183, 2000.

[3] S. S. Haykin. *Kalman filtering and neural networks.* Wiley Online Library, 2001.

[4] E. N. Lorenz. *Deterministic nonperiodic flow. J. Atmos. Sci.*, 20: 130141, 1963.

[5] T. Schön, F. Gustafsson and P. J. Nordlund. *Marginalized particle filters for mixed linear/nonlinear state-space models. IEEE Transactions on Signal Processing*, 53:2279–2289, 2005.

[6] D. Simon. *Optimal state estimation: Kalman, H_∞ and nonlinear approaches.* John Wiley and Sons, 2006.

[1]ÚTIA AV ČR, Department of Adaptive Systems, *hofman@utia.cas.cz*
[2]ÚTIA AV ČR, Department of Adaptive Systems, *dedecius@utia.cas.cz*