



Advanced Data Assimilation in strongly nonlinear systems

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Data assimilation workshop at Banff, Feb 3-8

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- Sigma-point Kalman filters
- Simulations with Lorenz model
- A Reduced SPKF
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Introduction

Data assimilation – a dynamical state space estimate problem

State equation $x_k = f(x_{k-1}, u_k); \quad (1)$

Observation equation $y_k = h(x_k, v_k) \quad (2)$

where x_k is state vector at time k , f state transition function, and u_k process noise with known distribution; y_k is observations at time instant k , h observation function, and v_k observation noise with known distribution.

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Statistical estimation

KF & EKF

Analysis step $\hat{x}_k = \hat{x}_k^- + K_k (y_k - E(h(\hat{x}_k^-, v_k))),$

$P_{x_k} = (I - K_k H_k) P_{x_k}^-$

$K_k = P_{x_k}^- H_k^T [R_k + H_k P_{x_k}^- H_k^T]^{-1}$

The forecast step $\hat{x}_k^- = E[f(\hat{x}_{k-1}, u_{k-1})],$

$P_{x_k}^- = L_{k-1} P_{x_{k-1}} L_{k-1}^T + Q_{k-1}$

$Q_k = E[(u_k - \bar{u}_k)(u_k - \bar{u}_k)^T],$

$R_k = E[(v_k - \bar{v}_k)(v_k - \bar{v}_k)^T]$

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Statistical estimation

EnKF--- Popular approach

Analysis step $\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\mathbf{y}_k - \mathbf{E}(\mathbf{h}(\hat{\mathbf{x}}_k^-, \mathbf{v}_k))),$
 $\mathbf{K}_k = \mathbf{P}_{x_k}^- \mathbf{H}_k^T [\mathbf{R}_k + \mathbf{H}_k \mathbf{P}_{x_k}^- \mathbf{H}_k^T]^{-1}$

The forecast step $\hat{\mathbf{x}}_k^- = \mathbf{E}[f(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1})],$
 $\mathbf{P}_{x_k}^- = \mathbf{E}[(\hat{\mathbf{x}}_k^- - \bar{\mathbf{x}})(\hat{\mathbf{x}}_k^- - \bar{\mathbf{x}})^T]$

Linear assumption for measurement function.

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Statistical estimation

EnKF--- classic approach

Analysis step $\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\mathbf{y}_k - \mathbf{E}(\mathbf{h}(\hat{\mathbf{x}}_k^-, \mathbf{v}_k))),$
 $\mathbf{P}_{x_k} = \mathbf{P}_{x_k}^- - \mathbf{K}_k \mathbf{P}_{y_k} \mathbf{K}_k^T$
 $\mathbf{K}_k = \mathbf{P}_{x_k y_k} \mathbf{P}_{y_k}^{-1}$

The forecast step $\hat{\mathbf{x}}_k^- = \mathbf{E}[f(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1})],$
 $\mathbf{P}_{x_k y_k} = \mathbf{E}[(\hat{\mathbf{x}}_k^- - \bar{\mathbf{x}})(\mathbf{y}_k - \mathbf{E}(\mathbf{h}(\hat{\mathbf{x}}_k^-, \mathbf{v}_k)))^T]$
 $\mathbf{P}_{y_k} = \mathbf{E}[(\mathbf{y}_k - \mathbf{E}(\mathbf{h}(\hat{\mathbf{x}}_k^-, \mathbf{v}_k)))(\mathbf{y}_k - \mathbf{E}(\mathbf{h}(\hat{\mathbf{x}}_k^-, \mathbf{v}_k)))^T]$

No linear assumption for measurement function.

Ref: (Gelb, 1974)

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Sigma-point Kalman filter

- The SPKF makes use of a reformulated Kalman gain K and “chooses” the ensemble deterministically in such a way that it can capture the statistical moments of the nonlinear model accurately; in other words, the forecast error covariance equation is computed using deterministically chosen samples, called “sigma-points”.
- The SPKF algorithm has been successfully implemented in many areas like robotics, artificial intelligence, natural language processing, and global positioning systems navigation.

Ref: (Julier et al. 1995; Nørgad Magnus et al. 2000; Ito and Xiong 2000; Lefebvre et al. 2002; Wan and Van Der Merve 2000; Haykin 2001; Van der Merwe 2004, Van der Merwe and Wan 2001, M.).

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SP-Unscented Kalman filter

Unscented transformation (Julier et al. 1995; Julier 1998; Wan and Van Der Merve 2000; Julier 2002).

Consider the propagation of a L -dimensional random variable x through an arbitrary nonlinear function:

$$\varphi = g(x);$$

x has mean \bar{x} and covariance P_x

$$S_i = \{w_i, \chi_i\};$$

$$\chi_0 = \bar{x};$$

$$\chi_i = \bar{x} + (\sqrt{(L+k)P_x})_i,$$

$$\chi_i = \bar{x} - (\sqrt{(L+k)P_x})_i,$$

$$w_0 = \frac{k}{L+k} \quad i=0$$

$$w_i = \frac{1}{2(L+k)} \quad i=1, \dots, 2L$$

k is a scaling parameter

$$\psi_i = g(\chi_i);$$

the dimension of the state-space L increases, the radius of the sphere that bounds all the sigma-points increases as well.

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SP-UKF Algorithm

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Analysis step

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\mathbf{y}_k - \mathbf{h}(\hat{\mathbf{x}}_k^-)),$$

$$\mathbf{P}_{x_k} = \mathbf{P}_{x_k}^- - \mathbf{K}_k \mathbf{P}_{y_k} \mathbf{K}_k^T$$

$$\mathbf{K}_k = \mathbf{P}_{x_k y_k} \mathbf{P}_{y_k}^{-1}$$

Forecast step

$$\boldsymbol{\psi}_k^i = f(\boldsymbol{\chi}_k^i),$$

$$\hat{\mathbf{x}}_k^- = \sum_{i=0}^{2L} w^i \boldsymbol{\psi}_k^i$$

$$\mathbf{P}_{x_k}^- = \sum_{i=0}^{2L} w^i (\boldsymbol{\psi}_k^i - \hat{\mathbf{x}}_k^-)(\boldsymbol{\psi}_k^i - \hat{\mathbf{x}}_k^-)^T$$

Measurement step

$$\mathbf{Y}_k^i = \mathbf{h}(\boldsymbol{\chi}_k^i),$$

$$\hat{\mathbf{y}}_k^- = \sum_{i=0}^{2L} w^i \mathbf{Y}_k^i$$

$$\mathbf{P}_{y_k} = \sum_{i=0}^{2L} w^i (\mathbf{Y}_k^i - \hat{\mathbf{y}}_k^-)(\mathbf{Y}_k^i - \hat{\mathbf{y}}_k^-)^T$$

$$\mathbf{P}_{x_k y_k} = \sum_{i=0}^{2L} w^i (\boldsymbol{\psi}_k^i - \hat{\mathbf{x}}_k^-)(\mathbf{Y}_k^i - \hat{\mathbf{y}}_k^-)^T$$

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SP-Central Difference KF

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- In SP-CDKF the analytical derivatives in EKF are replaced by numerically evaluated central divided differences, based on Sterling's polynomial interpolation.

(Ito and Xiong 2000; Nørnga°d Magnus et al. 2000; Lefebvre et al. 2002).

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Lorenz model

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$$\frac{dx}{dt} = \sigma(y - x) + q^x$$

$$\frac{dy}{dt} = \rho x - y - xz + q^y$$

$$\frac{dz}{dt} = xy - \beta z + q^z$$

True value: integrate the model over 4000 time steps using prescribed parameters and initial conditions.

Observation: true value plus normal distribute noise;

Experimental conditions are the same as those used by Miller (Miller, 1994) and Evensen (Evensen 1997)

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Lorenz model: state estimation

Observation and initial conditions: their true values plus normal distributed noise $N(0, \sqrt{2})$. The assimilation interval is 25 time steps.

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$$Error = \frac{1}{N} (x_k - x_k^{true})^2$$

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EnKF with 19 members

(a)

Assimilation Method	Computation Time (in Seconds)	RMSE
EKF	37.04	1.812
EnKF (with 1000 ensembles)	7143.57	1.987
EnKF (with 19 ensembles)	132.77	6.123
SP-UKF	133.91	1.640
SP-CDKF	90.42	1.592

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Stronger noise (10 times)

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Strong noise + Less observations

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Parameter estimation

- If the measurement function is nonlinear, it has to be linearized in the EnKF.


$$\Lambda_k = \Lambda_{k-1} + q_{k-1}$$

$$y_k = f(x_k, \Lambda_k) + r_k$$

where $f(\cdot)$ is the nonlinear measurement model given by the Lorenz equations, and Λ is the parameter vector which constitutes the dynamical parameters σ , ρ and β

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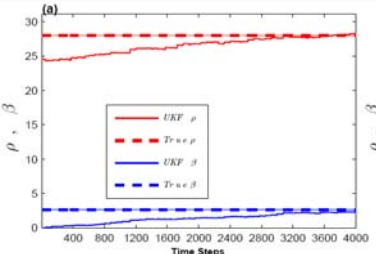
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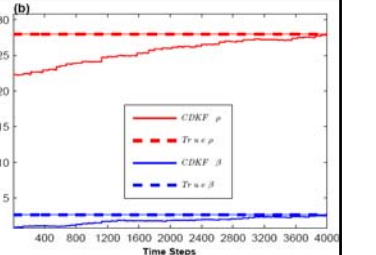
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Parameter estimation

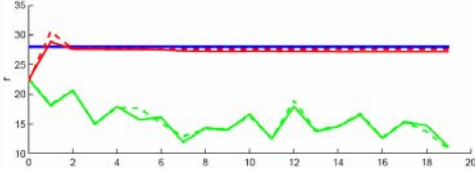
Initial parameters: true parameters plus normal distributed noise of covariance 100. Two parameters are estimated:



(a)



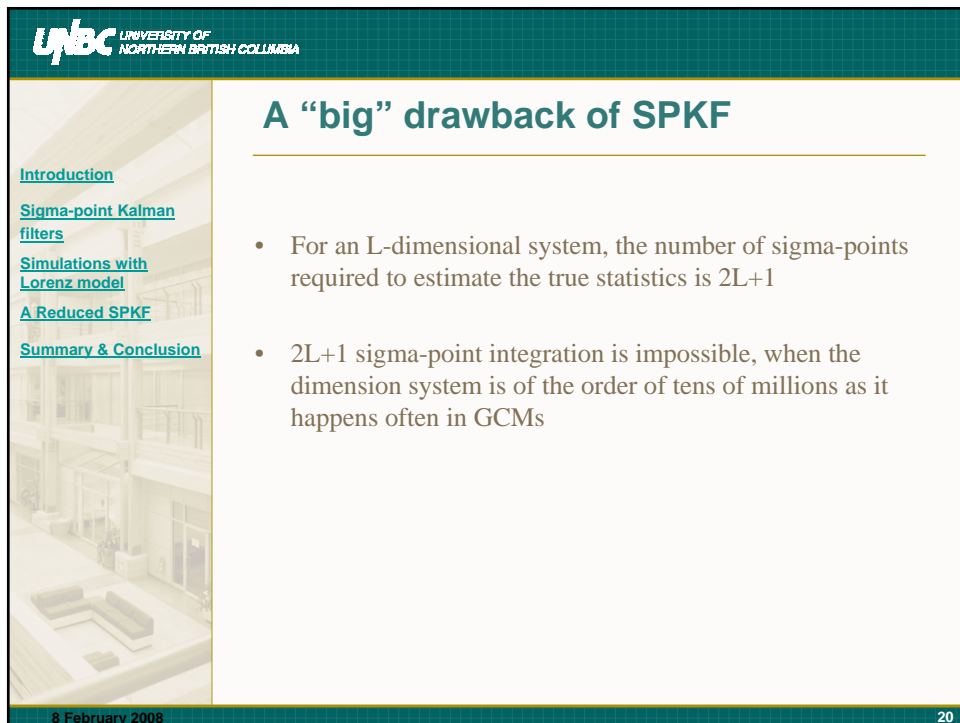
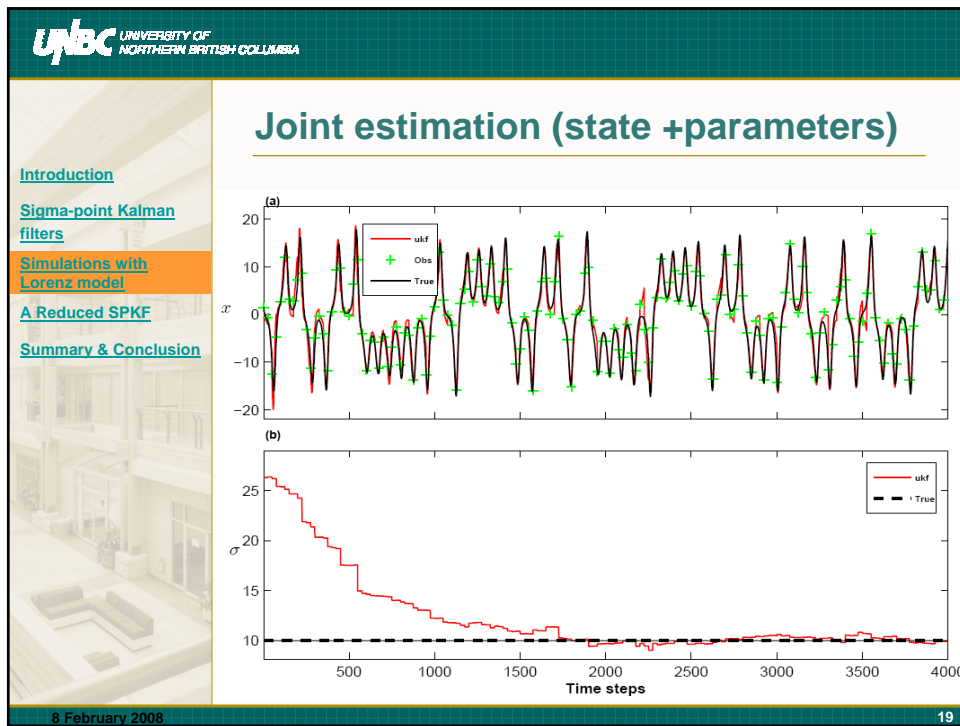
(b)




Kivman, G.A. 2003: Sequential parameter estimation for stochastic system, Nonlinear. Process. in Geophysics, 10, 253-259.

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A Possible solution – reducing sigma-points

$$S_i = \{w_i, \chi_i\};$$


$$\chi_0 = \bar{x};$$

$$\chi_i = \bar{x} + (\sqrt{(L+k)P_x})_i,$$

$$\chi_i = \bar{x} - (\sqrt{(L+k)P_x})_i$$

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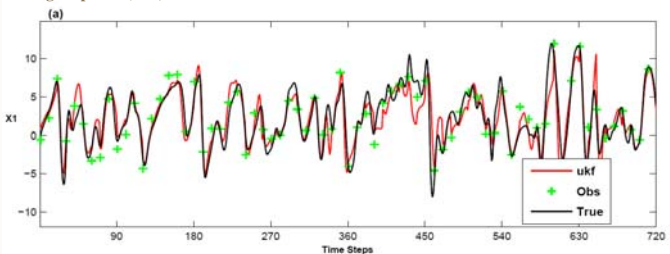
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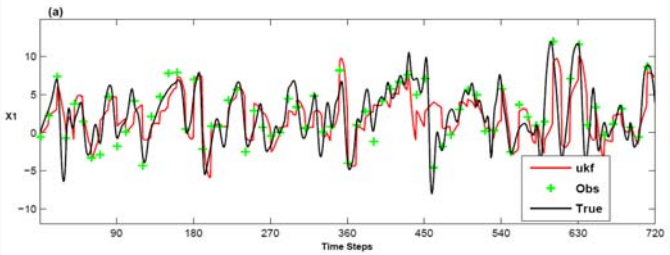
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A Reduced Sigma-point KF - (Lorenz '96 model)

with Full Sigma-points (241)



with reduced Sigma-points (100)



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Reduced sigma-points

with reduced Sigma-points (20)

(a)

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Conclusions

- The SPKF is a technique for a derivative-less optimal estimation using a deterministic sampling approach that ensures accurate estimation of error statistics.
- The SPKF is capable of estimating model state and parameters with better accuracy than EKF and EnKF for strong nonlinear systems.
- The SPKF is practically difficult for high dimensional systems. A possible solution is to reduce the number of sigma-points by “selecting a particular set of sigma-points”.

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