micro and nanoelectronics microsystems ambient intelligence image chain biology and health

Sensor fusion with intermittent data, application to attitude estimation

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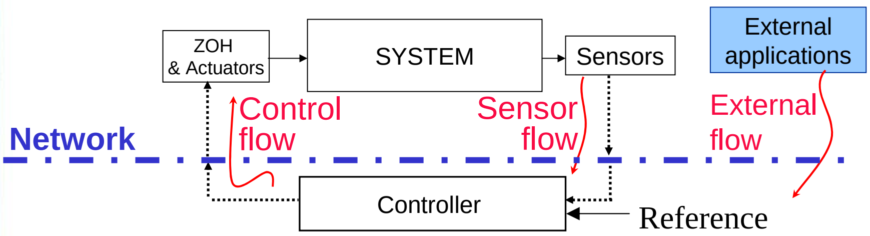
- Formerly: Professor in Grenoble University
  - Head of Electrical Engineering dpt (Bachelor level)
  - Head of Research Team SA-IGA on FDI
- Joined last month CEA-LETI MINATEC
- From the “process control” community
  - Sensor fusion, “Intelligent” sensors
  - FDI for industrial processes (arcing fault, rolling mill,…)
  - Estimation for NCS
  - EndUser of SoC, MPSoC → qualities
    - Linear algebra, FIR filters, Monte Carlo simulation, Monte Carlo like techniques (UKF, particle filter)

Contents

- Problem position
  - NCS, SN, WSN → control & estimation ?
  - Network and its drawbacks
- Observer
  - Kalman filtering
- **Estimation over a network**
  - Drawbacks
    - Distributed estimation
    - Data loss
    - Partial loss
  - Application
- Remarks

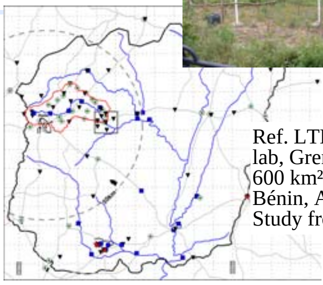
Problem position: NCS



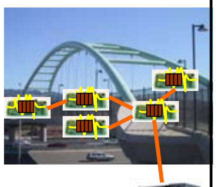
- Control of a plant with feedback loop
- Introduce a network
  - Wire simpler, maintenance, lower weight, lower cost…
  - Few influence
- Network shared
  - **Performances** of the Network controlled system?

Problem position: SN, WSN

- Monitoring of rainfall, environment, bridges, avalanche area, …



Ref. LTHE lab, Grenoble
600 km²
Bénin, Africa
Study from



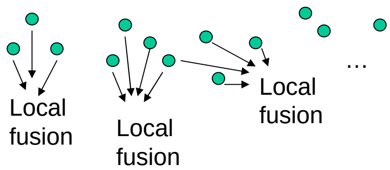
- Data collection
  - Network with wire
  - Wireless network

Ref. Sukun Kim et al., "Health Monitoring of Civil Infrastructures Using Wireless Sensor Networks" University of California at Berkeley, Crossbow Technology, Inc. SensorNet Architecture meeting, Nov 16, 2006

Problem position: SN, WSN

- Requirements
  - High fidelity data
  - High sampling frequency with low jitter
  - Autonomous → battery monitoring
  - Synchronization of acquisition
- Processing
  - Right at the sensors?
  - Local fusion?
  - Centralized fusion?
- Decision
  - Transfer raw data? High level data? Partial information?

Chicken and egg story



Network as a component of the system

- Shared with other applications
  - Cannot be ignored
  - Scheduling policy of the messages to be sent
- Drawbacks
  - Jitters, Delays
  - Packet/data losses …
- Safe functioning of the NCS
  - Appropriate protocols
  - Both controller and observer sides
    - Adapt existing algorithms / propose new algorithms

No decrease of the controlled system performances even in presence of a network

MPSoC cooling control

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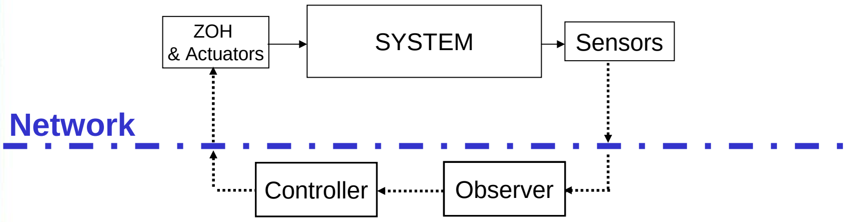
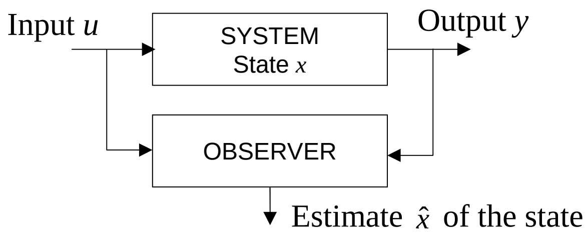
Observer / sensor fusion



- Measures → not all the variables of interest for the system
- State
- Implement an observer → where?

Observer: definition



- State observer

  provides an estimate of the internal state of a system from its inputs and outputs

$$\dot{x}(t) = f\left(x(t), u(t)\right)$$
$$y(t) = g\left(x(t)\right)$$

Observer

- Luenberger
- **Kalman Filter**
- Extended KF(EKF), Unscented KF (UKF)
- NL observer
- Set membership observer (Interval analysis)
- Particle filters …

$$\dot{x}(t) = f\left(x(t), u(t)\right)$$
$$y(t) = g\left(x(t)\right)$$

Literature well established
Strong properties

Kalman Filtering

- Linear discrete-time model

$$\begin{cases} x_{t+1} = A_t x_t + B_t u_t + v_t \\ y_t = C_t x_t + D_t u_t + w_t \end{cases}; M_t = \operatorname{cov}\left(\left[v; w\right]\right) = \begin{bmatrix} Q_t & S_t \\ S_t^T & R_t \end{bmatrix} \geq 0$$

- Hypotheses:
  - v,w independent from the past of $u,x,y,$
  - v,w gaussian independent white noises sequences, with zero mean
  - $S = 0, D = 0$

$$\begin{cases} \hat{x}_{t/t}, P_{t/t} \text{ estimate of } x_t \text{ and its covariance} \\ \hat{x}_{t/t-1}, P_{t/t-1} \text{ prediction of } x_t \text{ and its covariance} \end{cases}$$

Kalman Filtering

- **Prediction stage**

$$\hat{x}_{t+1/t} = A_t \hat{x}_{t/t} + B_t u_t ; \quad P_{t+1/t} = A_t P_{t/t} A_t^T + Q_t$$

- **Correction stage**

$$\begin{cases} \hat{x}_{t+1/t+1} = \hat{x}_{t+1/t} + P_{t+1/t} C_{t+1}^T \left(C_{t+1} P_{t+1/t} C_{t+1}^T + R_{t+1} \right)^{-1} \left(y_{t+1} - C_{t+1} \hat{x}_{t+1/t} \right) \\ P_{t+1/t+1} = P_{t+1/t} - P_{t+1/t} C_{t+1}^T \left(C_{t+1} P_{t+1/t} C_{t+1}^T + R_{t+1} \right)^{-1} C_{t+1} P_{t+1/t} \end{cases}$$

- **Numerical difficulties**
  - Satisfy numerically the property $P = P^T \geq 0$

Kalman Filtering

- **Square root form (factorized)**

$$\left(Q_t^{1/2}\right)^T Q_t^{1/2} = Q_t \ , \ \left(R_t^{1/2}\right)^T R_t^{1/2} = R_t \text{ and } \left(P_t^{1/2}\right)^T P_t^{1/2} = P_t$$

Prediction

QR factorization

$$\hat{x}_{t+1/t} = A_t \hat{x}_{t/t} ; H \begin{bmatrix} Q_t^{1/2} \\ P_{t/t}^{1/2} A_t^T \end{bmatrix} = \begin{bmatrix} P_{t+1/t}^{1/2} \\ 0 \end{bmatrix}$$

Estimation/correction

$$\begin{cases} H \begin{bmatrix} R_{t+1}^{1/2} & 0 \\ P_{t+1/t}^{1/2} C_{t+1}^T & P_{t+1/t}^{1/2} \end{bmatrix} = \begin{bmatrix} U & Z \\ 0 & P_{t+1/t+1}^{1/2} \end{bmatrix} ; G_{t+1} : U G_{t+1}^T = Z \\ \hat{x}_{t+1/t+1} = \hat{x}_{t+1/t} + G_{t+1} \left[y_{t+1} - C_{t+1} \hat{x}_{t+1/t} \right] \end{cases}$$

Kalman Filtering

- **Relax hypotheses**
  - Noise *v,w*
  - Non linear model → Extended Kalman Filter

  → Loss of optimality properties

$$\begin{cases} x_{t+1} = f(t, x_t) \\ y_t = g(t, x_t) \end{cases} \qquad \begin{cases} x_{t+1} = A_t x_t + v_t \\ y_t = C_t x_t + w_t \end{cases}$$

Linearize around the most recent state estimate

$$A_t = \left.\frac{\partial f(t, x_t)}{\partial x_t}\right|_{x=x_t} \qquad C_t = \left.\frac{\partial g(t, x_t)}{\partial x_t}\right|_{x=x_t}$$

UKF

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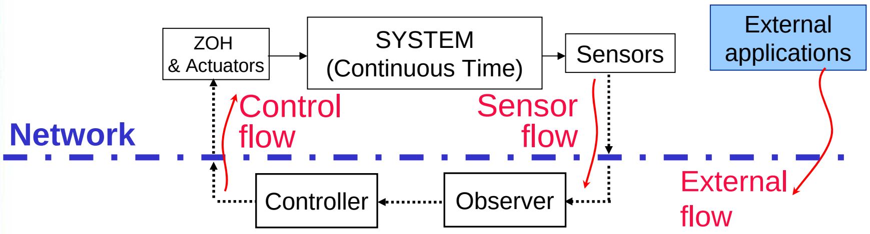
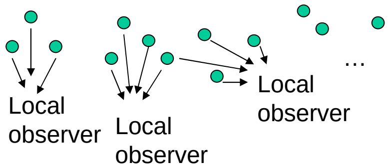
Estimation over a network



- Distributed system → Distributed estimation?
- Data desynchronisation
- Data loss

Distributed system and distributed estimation

- Right at a set of sensors (without communication)
- Low range exchange between the sensor and the observer

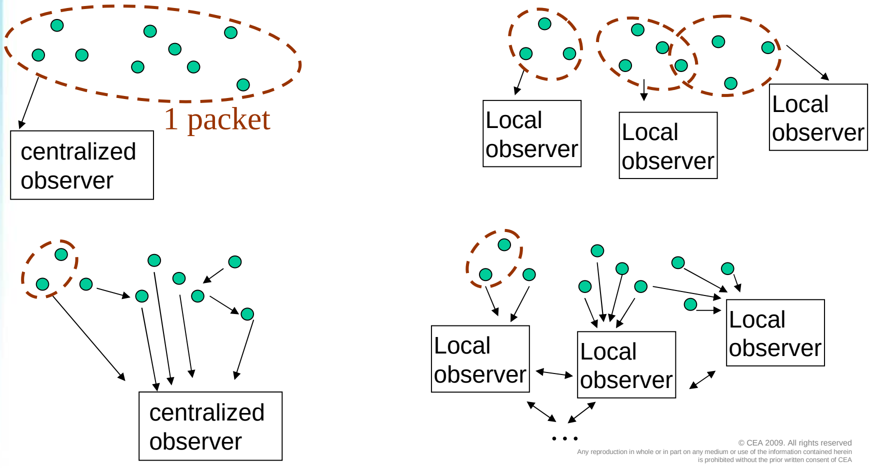


[1] Alriksson & Rantzer, 2008
→ Distributed Kalman Filter
[2] Shi, Johansson & Murray, 2008
→ **Tradeoff** between com., comp. and estim. qualities
[3] Olfati-Saber, 2007
→ **Distributed Kalman filter**
[4] S. Stankovic, M. Stankovic & D. Stipanovic, 2009
→ Distributed Kalman Filter, loss
. .

Estimation with data loss

Data loss

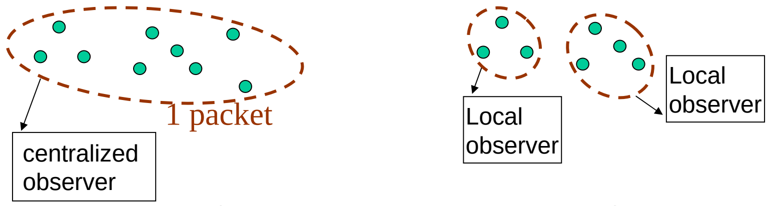
- In both estimation schemes: centralized/distributed



Estimation with data loss

Classical Hypotheses

- All sensor reading in a unique packet



(Ref. [5],[6],[7],[8],[9],[10] and ref. therein)

- Packet loss model
  - Bernouilli / Markov chain
  - → Convergence properties of E[P]

Estimation with data loss

- **Prediction phase**

$$\begin{cases} \hat{x}_{t+1/t} = A_t \hat{x}_{t/t} \\ P_{t+1/t} = A_t P_{t/t} A_t^T + Q_t \end{cases}$$

- **Model of the system**

$$x_{t+1} = A_t x_t + w_t$$
$$y_t = C_t x_t + v_t$$

- **Correction phase**

$$K_{t+1} = P_{t+1/t} C_{t+1}^T \left[C_{t+1} P_{t+1/t} C_{t+1}^T + R_{t+1} \right]^{-1}$$

$$\begin{cases} \hat{x}_{t+1/t+1} = \hat{x}_{t+1/t} + \gamma_{t+1} K_{t+1} (y_{t+1} - C_{t+1} \hat{x}_{t+1/t}) \\ P_{t+1/t+1} = P_{t+1/t} - \gamma_{t+1} K_{t+1} C_{t+1} P_{t+1/t} \end{cases}$$

Implement the factorized version!

$\gamma = 1$, sensor readings received → correction done

$\gamma = 0$, sensor readings not received, no correction, only prediction

Estimation with **partial** data loss

- **Main limitation**
  - All sensor readings in one message

- **Partial loss [11][12]**

$$\begin{array}{lll} M_t(i,j) & = 0 & \text{if } i \neq j \\ M_t(i,i) & = 1 & \text{if the measure } y_i \text{ has been received} \\ M_t(i,i) & = \lambda_i >> 1 & \text{if the measure } y_i \text{ has not been received} \end{array}$$

missing data → 0, previous value…

→ larger variance $\bar{\sigma}_i^2 = \lambda_i^2 \sigma_i^2$

Covariance matrix with partial loss

$$\bar{R}_t = M_t R_t M_t$$ Change the confidence in y_i

Estimation with partial data loss

- Initialization
  - Initial state $\hat{x}_0$, initial covariance matrix $\begin{cases} P_0 = \lambda I \\ \lambda >> 1 \end{cases}$
- Prediction step

$$\hat{x}_{t+1/t} = A_t \hat{x}_{t/t} \quad P_{t+1/t} = A_t P_{t/t} A_t^T + Q_t$$

- Computation of the gain matrix

$$\overline{K}_{t+1} = P_{t+1/t} C_{t+1}^T [C_{t+1} P_{t+1/t} C_{t+1}^T + \overline{R}_{t+1}]^{-1} \qquad \overline{R}_t = M_t R_t M_t$$

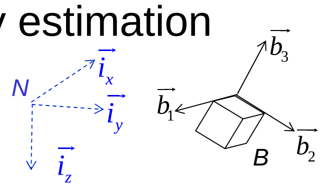
- Correction step

$$\begin{cases} \hat{x}_{t+1/t+1} = \hat{x}_{t+1/t} + \overline{K}_{t+1}(y_{t+1} - C_{t+1}\hat{x}_{t+1/t}) \\ P_{t+1/t+1} = P_{t+1/t} - \overline{K}_{t+1} C_{t+1} P_{t+1/t} \end{cases}$$

Factorized version obvious

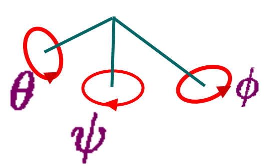
Estimation over a network: **application**

- Attitude of a rigid body estimation
  - Inertial frame *N*
  - Body frame *B*



- Express coordinates of $\vec{b}$ in *N*
  - Angles

$$\vec{r} = C(\phi, \theta, \psi)\vec{b}$$



  - Unitary quaternion q : $|| q || = 1$

$$q = \begin{bmatrix} q_0 & \vec{q}^T \end{bmatrix}^T \in \Re^4$$

Estimation over a network: application

- IMU: MAG3 Memsense
  - no computation capability right at the sensors
  - network

3 modalities:

- 3 rate gyros
  $\vec{\omega}_g = \vec{\omega} + \vec{\eta}_g \in \Re^3$
- Triaxis Accelerometer
  $\vec{b}_a = C(q)\left(\vec{a} - \vec{g}\right) + \vec{\eta}_a \in \Re^3$
- Triaxis Magnetometer
  $\vec{b}_m = C(q)\vec{h} + \vec{\eta}_m \in \Re^3$

0.7in*0.7in*0.4in

Measurement equation

$$y = \begin{pmatrix} \vec{b}_a \\ \vec{b}_m \end{pmatrix} \in \Re^6$$

Estimation over a network: application

- Kinematic equation $\dot{q} = \frac{1}{2}\Xi(q)\vec{\omega} = \frac{1}{2}\Omega(\vec{\omega})q$

$$\Xi(q) = \begin{bmatrix} -q^T \\ q_0 I + [\vec{q}^\times] \end{bmatrix}, \Omega(\vec{\omega}) = \begin{bmatrix} 0 & -\vec{\omega}^T \\ \vec{\omega} & -\vec{\omega}^\times \end{bmatrix}, \vec{\omega}^\times = \begin{bmatrix} 0 & -\omega_3 & \omega_2 \\ \omega_3 & 0 & -\omega_1 \\ -\omega_2 & \omega_1 & 0 \end{bmatrix}$$

- Discrete time version

$$q_{t+1} = f(q_t) = A_t q_t$$

$$A_t = \exp\left(\frac{1}{2}\Omega(\vec{\omega}_t)T_e\right)$$

$$y_t = g(q_t) = \begin{pmatrix} \vec{b}_{a,t} \\ \vec{b}_{m,t} \end{pmatrix} \in \Re^6$$

Actually
$\vec{\omega}_{gt} = \vec{\omega}_t + \vec{\eta}_{gt}$

Estimation over a network: application

$$\vec{\omega}_t = \vec{\omega}_{gt} + \vec{\eta}_{gt} \quad \longrightarrow \quad F_t = F_{gt} + \Delta F_t$$

$$F_{gt} = \exp\left(\frac{1}{2}\Omega(\vec{\omega}_{gt})T_e\right) \qquad \Delta F_t = \frac{1}{2}\Omega(\vec{\eta}_{gt})T_e$$

Error matrix

$$\boxed{\begin{aligned} q_{t+1} &= F_{gt}q_t + \vec{\eta}_{qt} \\ \vec{\eta}_{qt} &= \tfrac{T_e}{2}\Xi(q_t)\vec{\eta}_{gt} = G_t\vec{\eta}_{gt} \end{aligned}}$$

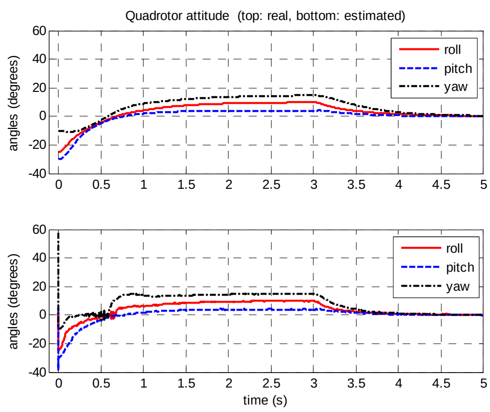
State covariance matrix (no more diagonal!)

$$Q_t = \frac{T_e^2}{4}\Xi(\hat{q}_t)R_{Gt}\left(\Sigma(\hat{q}_t)\right)^T + \frac{T_e^2}{4}\Upsilon\left[R_{Gt}\otimes P_t\right]\Upsilon^T$$

$\otimes$ Kronecker product, $\Upsilon = [\Omega(\vec{e}_1)\ \ \Omega(\vec{e}_1)\ \ \Omega(\vec{e}_1)]$

$(\vec{e}_1, \vec{e}_2, \vec{e}_3)$ orthonormal basis of $\Re^3$

Estimation over a network: application



Scenario

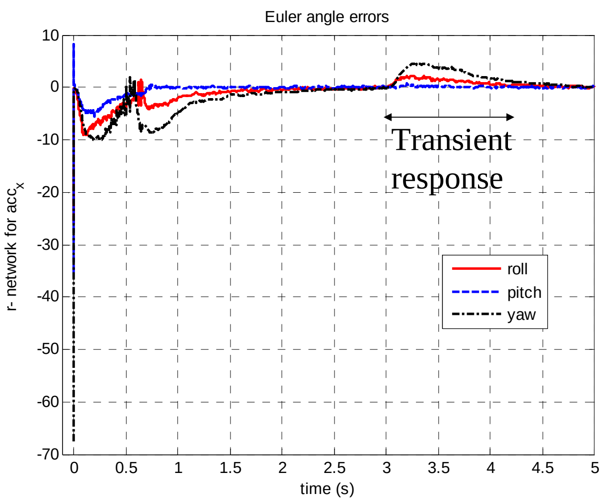
20% data loss on acc/mag

Reference changes from [-25;-30;-10]° to [10;4;15]°

Attitude filter is initialized with [-9.7;5.4;57.6]°

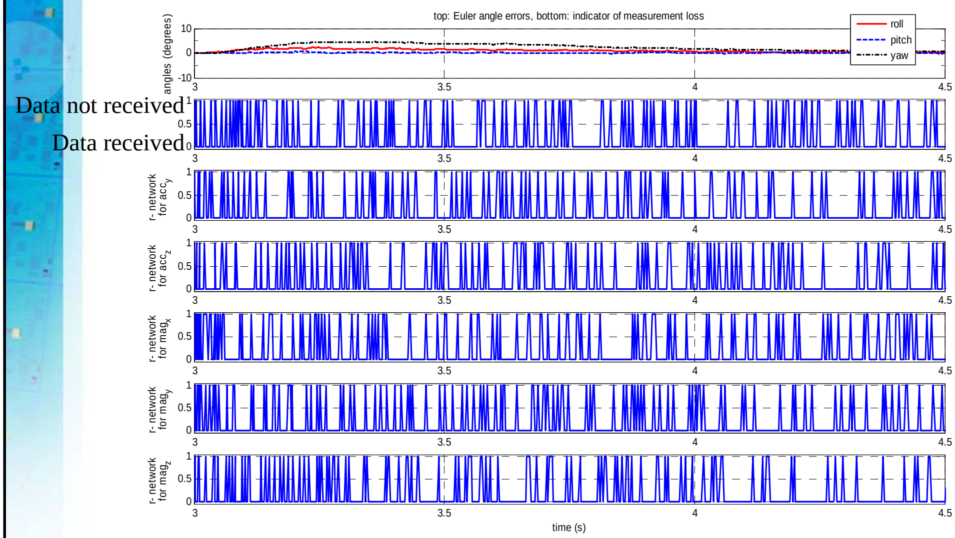
At time $t = 3s$, reference is [0;0;0]

Estimation over a network: application



Attitude error (in degrees)

Estimation over a network: application



Contents

Remarks / Needs for further research

- Computation distribution
  - Application dependant
  - Power consumption limitation (life duration)
  - Raw data / high level information transmission ?
- Data loss
  - Reliable global information? → needs for **supervision** of systems/processes, **control**
  - Protocol

Sensor fault
Broken communication
Data delays
Data desynchronisation

- Fault Tolerant Reliability (estimates robust against faults & data losses)
- Several communities together

Observation techniques for MPSoC

- **Estimation**
  - of parameters not measured
  - of parameters not measured in a particular location (e.g. temperature)
- **Observation techniques associated with control**
  - Control cooling
  - Performance management

References

[1] Alriksson & Rantzer, "Model based information fusion in sensor networks, IFAC WC 2008

[2] Shi, Johansson & Murray, "Estimation over wireless sensor networks:tradeoff between communication, computation an estimation qualities", IFAc WC 2008

[3] Olfati-Saber, "Distributed Kalman filtering for sensor networks", CDC2007

[4] S. Stankovic, M. Stankovic & D. Stipanovic, "Consensus based overlapping decentralized estimation with missing observations and communication faults", Automatica 2009

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[6] J. Hespanha, P. Naghshtabrizi, Y. Xu, "Networked control systems: analysis and design", *IEEE Network controlled systems*, 2007.

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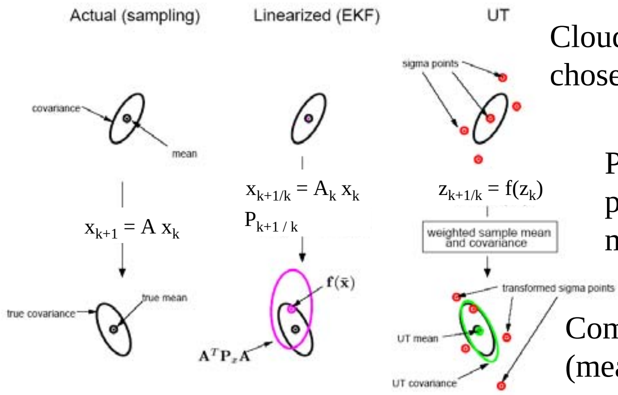
[10] M. Epstein, L. Shi, A. Tiwari, R. Murray, „ Probabilistic performances of state estimation across a lossy network, *Automatica*, Vol. 44, pp. 3046-3053, 2008.

[11] Lesecq S., Gentil S., Daraoui N,.”Quadrotor Attitude estimation with data losses”, European Control Conference ECC'09 Budapest, Hongrie (2009)

[12] S. Lesecq, S. Gentil, C. Berbra, “Condition monitoring based on filter bank in the presence of data loss”, Condition Monitoring Conference CM2009/MFPT2009, Dublin, June 2009.

Unscented Kalman Filter

- Natural parallel implementation



Cloud of carefully chosen points

Propagate the points with the model equation

Compute statistics (mean, covariance)

Ref.: Introduction to Kalman filtering, TRAIL Course on Kalman filtering
The Unscented Kalman Filter (UKF), Chapter 7a
Hao Liu, Ke Zhang, Delft University of Technology