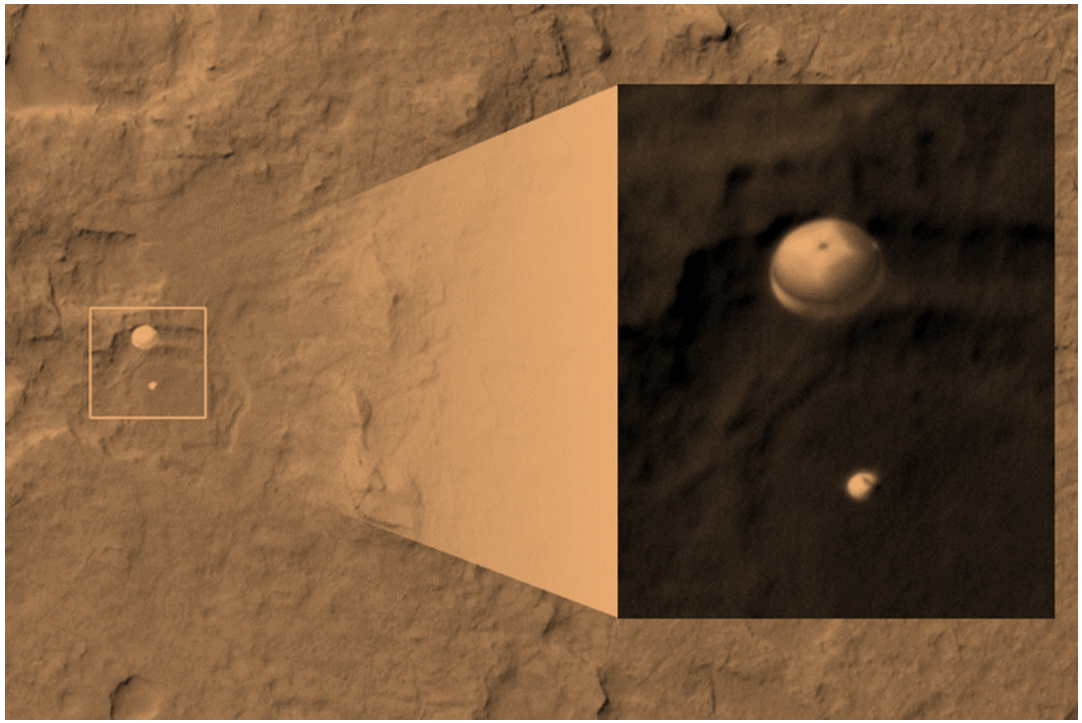
Mars EDL reconstruction from flight data: Uncertainty Quantification



Source [1]

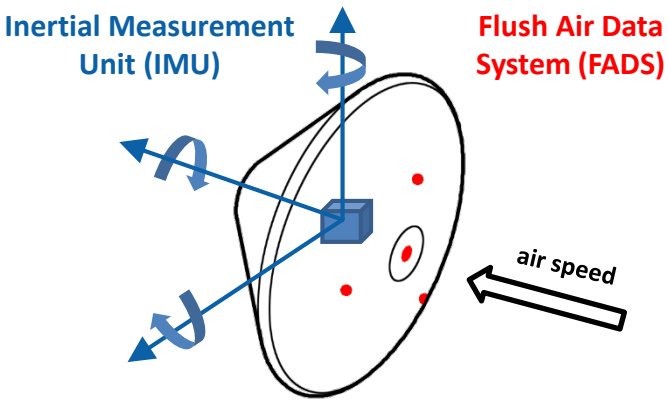
Bart Van Hove
Özgür Karatekin
(AMELIA ExoMars)

Royal Observatory of Belgium
Ringlaan 3, Brussel 1180
bartvh@observatory.be

11th International Planetary Probe workshop

Pasadena, US
19 June 2014

EDL post-flight reconstruction



flight data recorded during entry

Flush Air Data System (FADS) on 2016 ExoMars EDM engineering model adapted from [Y. Mignot et al., 2013]

Motives

- Mission critical phase: post-flight analysis
- Reconstruct trajectory & atmosphere

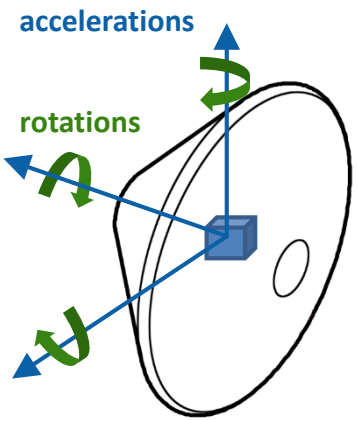
Mars entry flight data

- IMU: translational and angular velocity rates
- FADS: heat shield surface pressures

Some post-flight reconstruction results

- 2008 Phoenix: trim angle anomaly
  [Desai et al., 2011]
- 2008 Phoenix: large scale atmosphere oscillations consistent with thermal tides
  [Withers et al., 2010]
- 1997 Pathfinder atmosphere reconstruction suggested CO_2 clouds
  [Schofield et al., 1997 – Clancy et al., 1998]

IMU-based reconstruction – conventional methodology

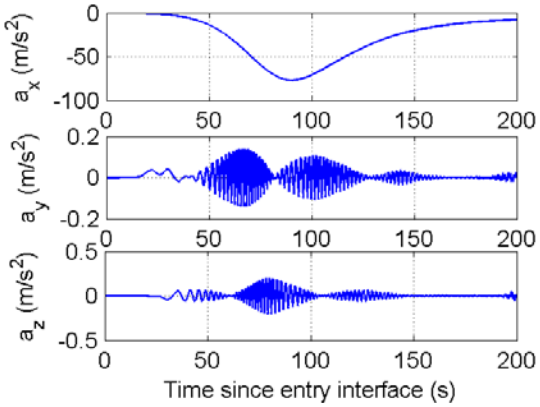


IMU flight data

Trajectory reconstruction

- Initial trajectory state
- Numerical integration of IMU acceleration and rotation rate signals (equations of motion)

UNCERTAINTY



simulated ExoMars inertial acceleration data

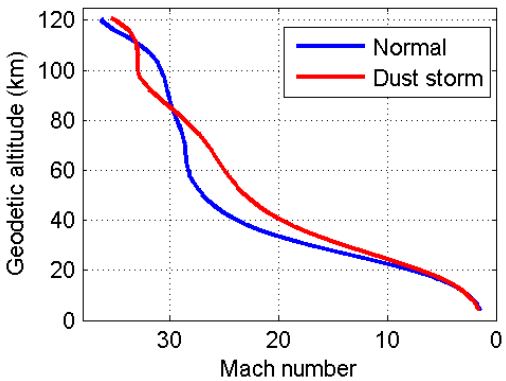
Atmosphere reconstruction

1. Derive density from acceleration and drag

$$\rho = 2\frac{m \cdot |\vec{a}|}{C_D \cdot A_{ref} \cdot V^2}$$

   Aerodynamic drag coefficient C_D

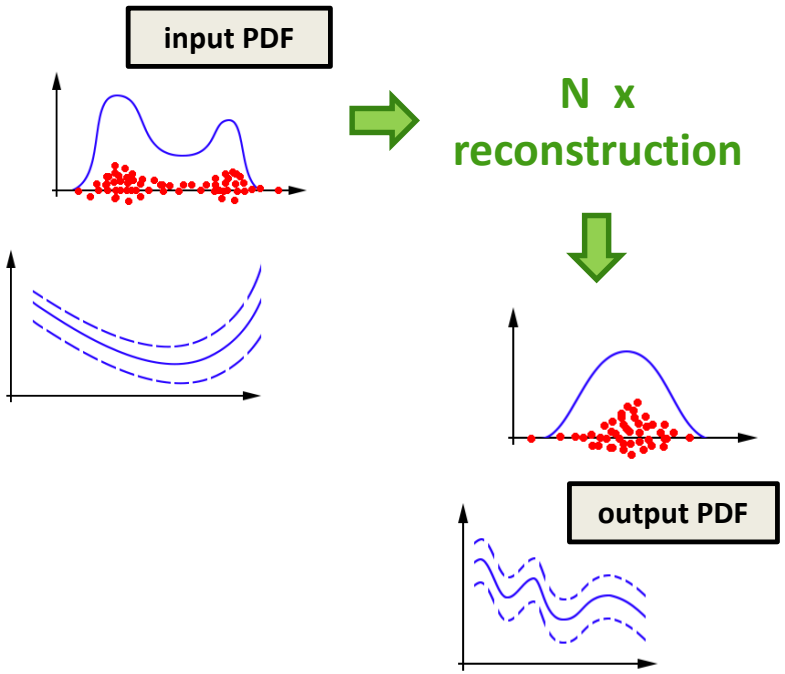
2. Derive pressure: integrate density over altitude (hydrostatic equilibrium from initial pressure)
3. Derive temperature: divide pressure by density (ideal gas law)



simulated ExoMars Mach-altitude profile

Monte Carlo (stochastic sampling)

- N samples from input probability density functions (PDF)
- N deterministic reconstructions
- For large >> N the output PDF can be well approximated
- Advantages: simple, robust, flexible



Bayesian state estimation (stochastic solver)

- Replaces deterministic reconstruction methodology
- Commonly a Kalman filter assuming white Gaussian noise
- Blends predictions (models) and observations (measurements)
- Provides reconstruction with uncertainty bounds
- Advantages: can be fast (real-time)
  can combine multiple measurements

Bayes' rule

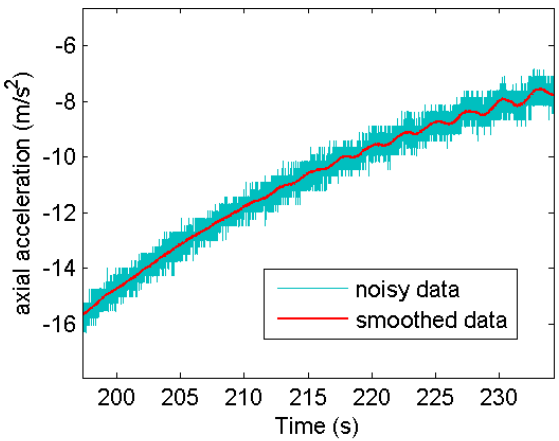
x state
z measurement

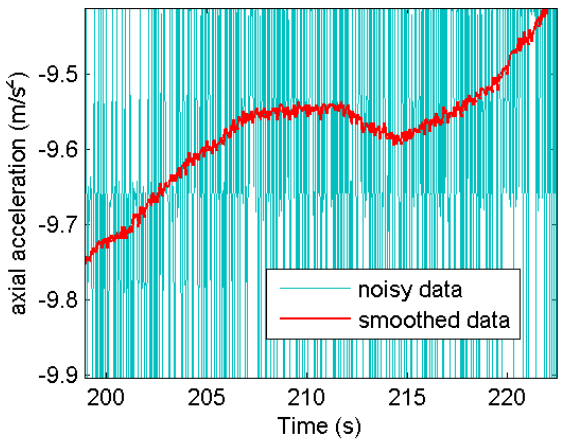
$$P(x|z_k) \sim P(z_k|x) \cdot P(x|z_{k-1})$$

state estimate | observation | prediction

Phoenix IMU flight data

- Available on PDS
- High sampling rate (200 Hz)





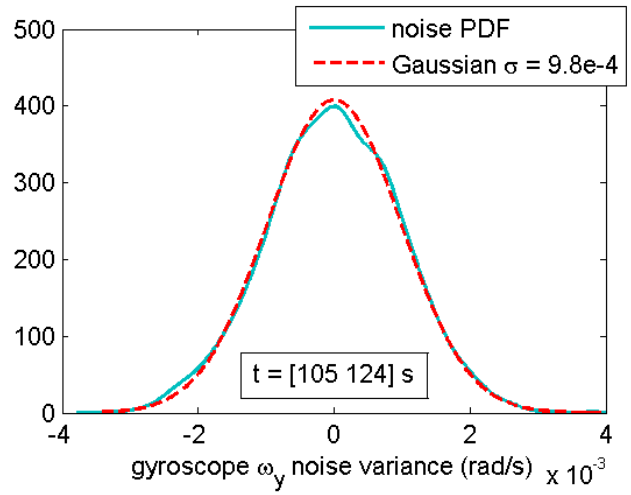
- What is the noise that was smoothed out like?
- Uncertainty associated with smoothed signal?
- Data noise description required in any UQ approach

what is the impact of noise characteristics and smoothing on UQ?

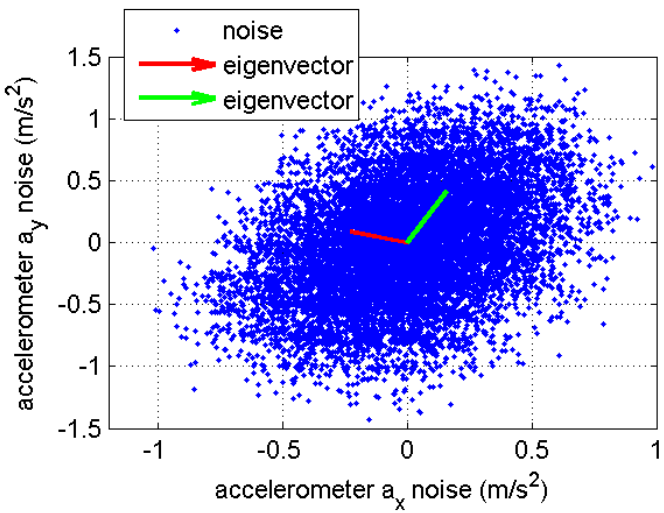
Phoenix IMU data noise characteristics

- Subtract smoothed signal from noisy data
- Construct detailed noise description
- Gaussian noise? Frequency content? Cross-correlations?
- The above stationary or function of time? (yes, nearly)
- Store complete description for noise generators to use

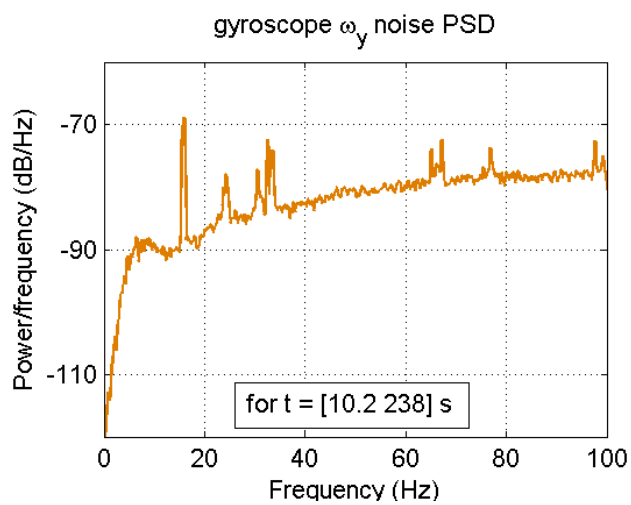
Gaussian data noise variance



cross-correlations between data noise



not exactly white: auto-correlated data noise

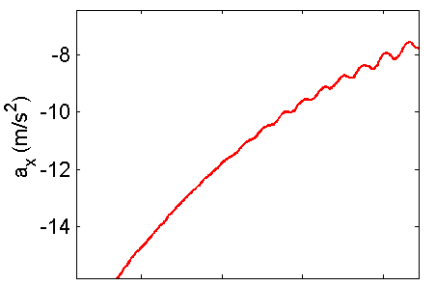


how important are these characteristics ?

Two ways to implement data noise

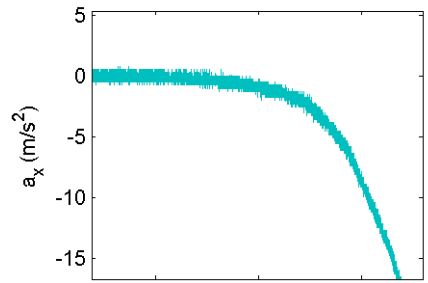
A Apply noise before smoothing

smoothed data



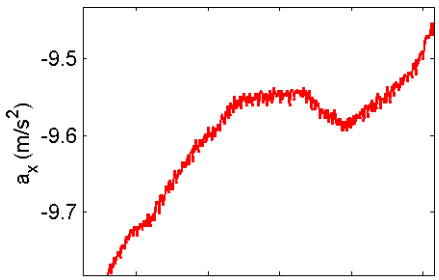
N x generate raw data noise

noisy data



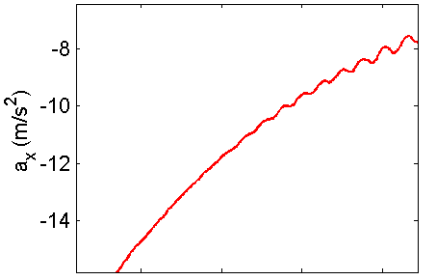
N x smooth noisy data

RECONSTRUCTION INPUT



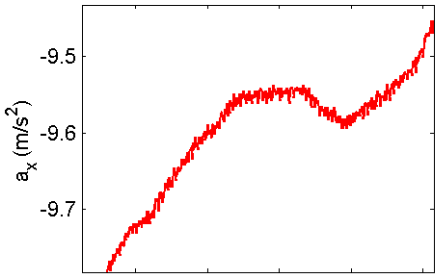
B Apply noise after smoothing

smoothed data



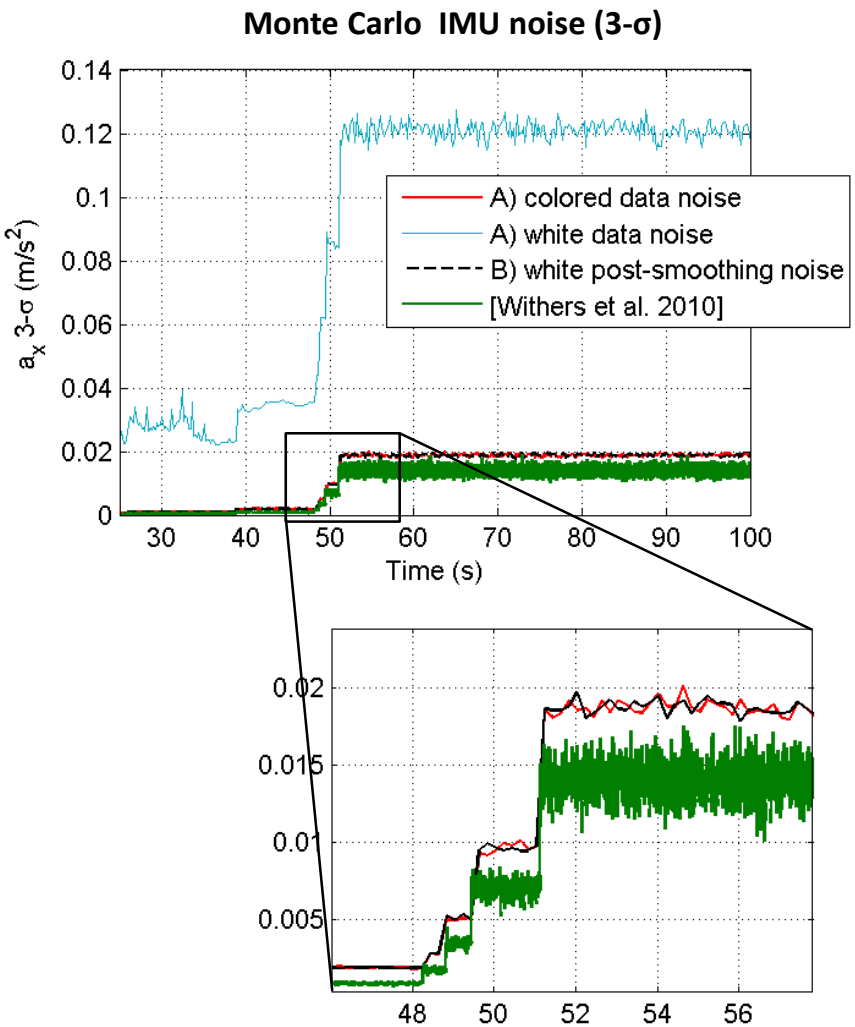
N x generate post-smoothing noise

RECONSTRUCTION INPUT



N x deterministic reconstruction

UQ: Monte Carlo reconstruction



A **Generate noise before smoothing**

Based on IMU noise analysis but assuming white noise:

- smoother less effective
- more post-smoothing noise

Generating colored data noise:

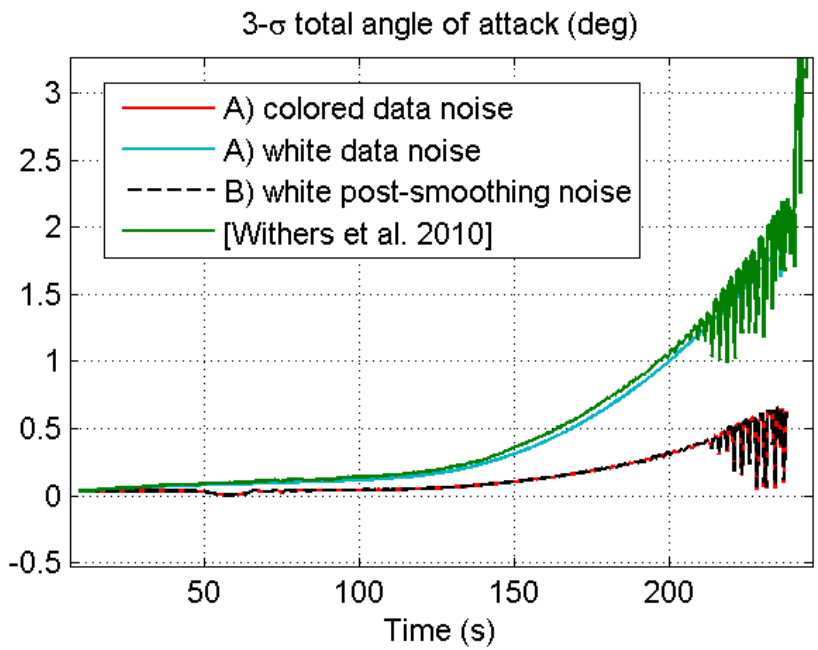
- smoother as effective as for real data
- less post-smoothing noise

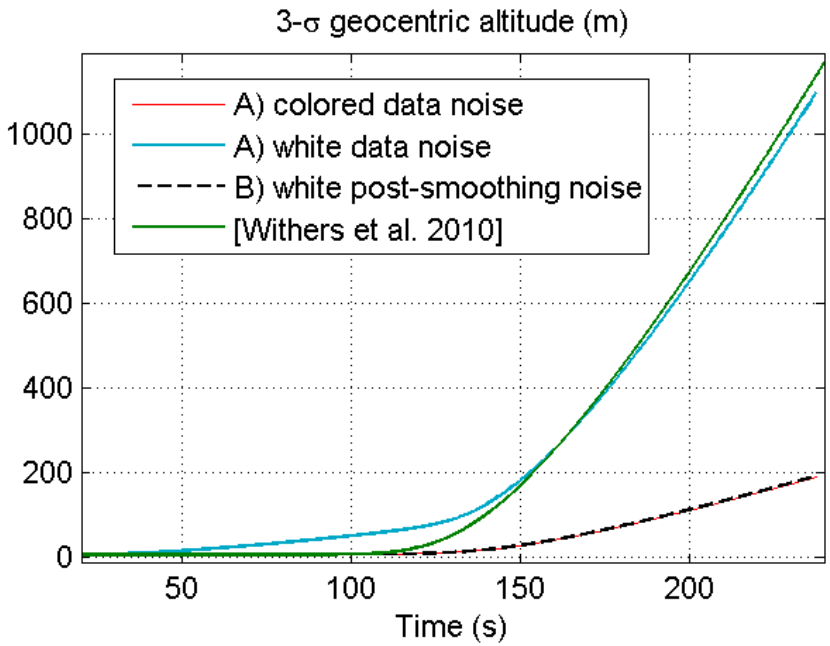
B **Generate noise after smoothing**

Assumed white post-smoothing noise

Used the post-smoothing noise variance estimated by A with colored noise

Monte Carlo reconstruction results for Phoenix





- Neglecting noise frequency content may overestimate reconstruction uncertainty
- In particular trajectory uncertainty bounds (mainly dependent on IMU noise)
- However negligible impact on atmosphere reconstruction (mainly C_D uncertainty)
- Neglecting cross-correlations had negligible impact (results not shown)

So far

Conclusions from Monte Carlo

- Carefully evaluate flight data noise regarding frequency content, cross-correlation and consequences for and of smoothing
- Phoenix IMU data is colored, cross-correlated and Gaussian
- PDS trajectory uncertainty was overestimated consistent with white noise assumptions

Consequences for state estimator design

- Kalman filters commonly assume white Gaussian noise (augmentations do exist)
- But operates differently from conventional deterministic reconstruction:

what is the impact of assuming white noise?

Preliminary Kalman results

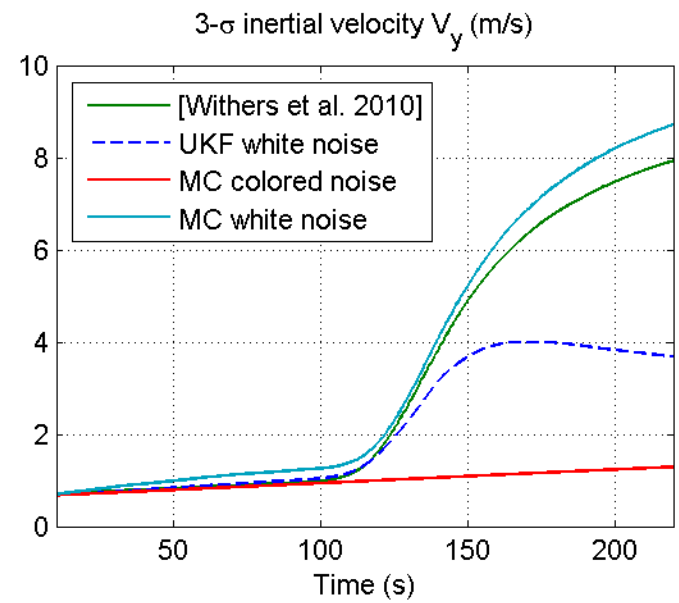
- Input unsmoothed IMU data
- IMU white noise description

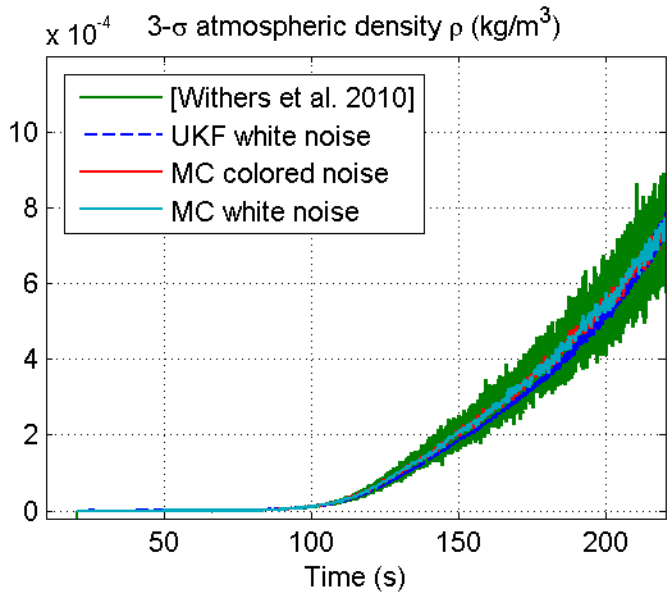
Trajectory reconstruction

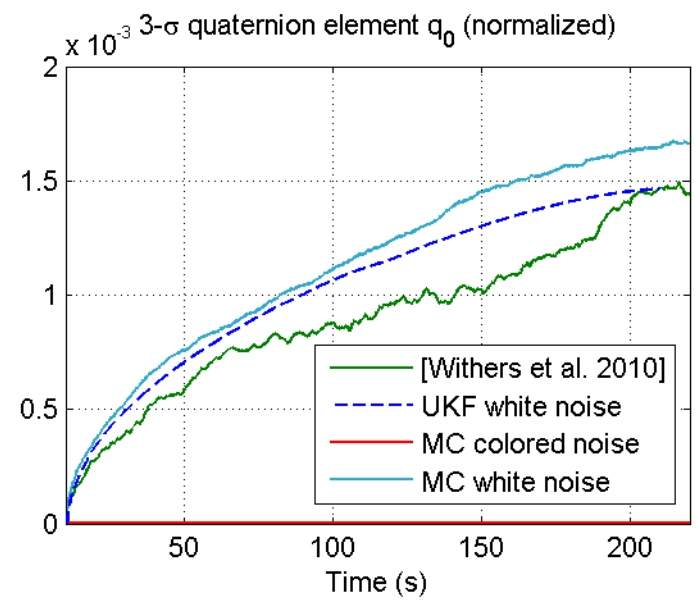
Similarities with white noise Monte Carlo overestimate

Atmosphere reconstruction

Insignificant impact of noise frequency content







Further questions for state estimation

Blending predictions and observations:

Predictive model uncertainty is often tuned to

- bias the filter to observational data or predictive models
- avoid numerical instabilities in the algorithm

But we prefer uncertainties to be based on physical or model validation arguments

How to compare EDL reconstruction with ground simulations when that reconstruction is influenced by expected results?

The detailed construction of prediction and measurement models affects uncertainty propagation:

which are most appropriate for science and engineering UQ purposes?

Conclusions

original question:

what is the impact of noise characteristics and smoothing on reconstruction UQ?

we showed that

- IMU data noise recorded by 2008 Phoenix is colored, cross-correlated and Gaussian
- Monte Carlo approaches require the signal frequency content to be taken into account
- white noise assumptions can work but must be justified and used carefully
- incorrect white noise assumptions overestimated trajectory uncertainties

preliminary results suggest that

- these conclusions also apply to Bayesian state estimators used for UQ
- Kalman solvers could benefit from colored noise models
- Different implementations produce different uncertainty estimates

References

[title image source]

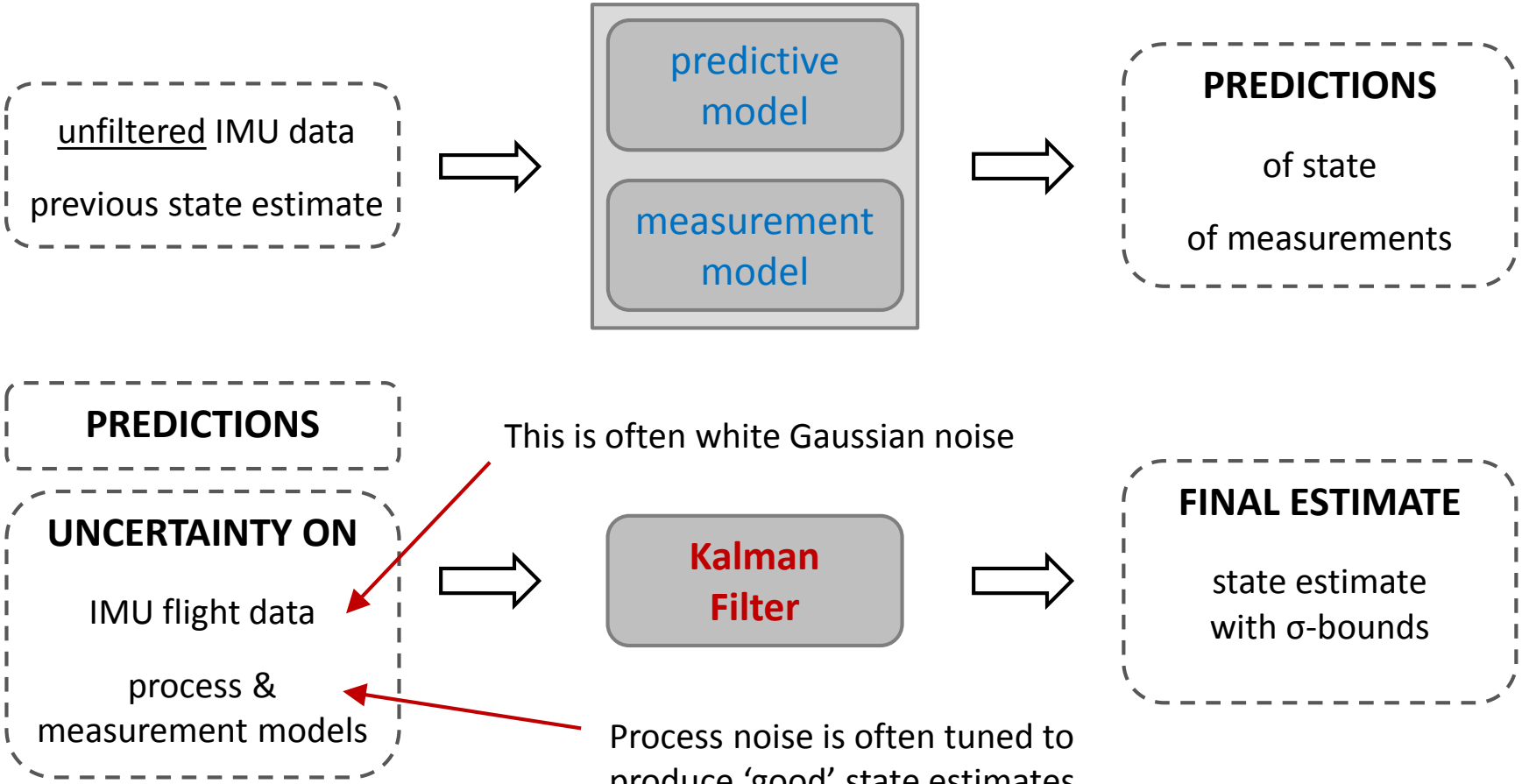
[Y. Mignot et al. 2013] An insight into EXOMARS EDM HS development, ESA TPS Workshop 7th edition, ESA ESTEC, Noordwijk, The Netherlands on 8-10 April 2013

[P. N. Desai et al. 2011] Entry, Descent, and Landing Performance of the Mars Phoenix Lander, J. of Spacecraft and Rockets, Vol. 48, No. 5

[P. Withers et al. 2010] Report in Planetary Data System (PDS), Phoenix Entry Profiles Data Archive (PHX-M-ASE-5-EDL-RDR-V1.0), 5 April 2010

[J. T. Schofield et al. 1997] The Mars Pathfinder Atmospheric Structure Investigation/Meteorology Experiment (ASI/MET), Science, 278, pp. 1752-1758

[R. T. Clancy & B. J. Sandor 1998] CO_2 ice clouds in the upper atmosphere of Mars, Geophys. Res. Letters, Vol. 25, No. 4, pp. 489-492

Blending prediction and observation

for every time step: