

Innovation vs Residual KF based GNSS/INS Autonomous Integrity Monitoring in Single Fault Scenario

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Knowledge for Tomorrow



Motivation

- IRS Systems integrated in Civil Aviation
 - Improve accuracy
 - Guarantee continuity
- In GNSS/INS, inertial can potentially also increase the fault detection capability to meet stringent requirements (e.g., CAT III, GBAS,..)
- GNSS/INS is now a baseline solution for new applications that operate in more challenging scenarios (Automotive, UAV)

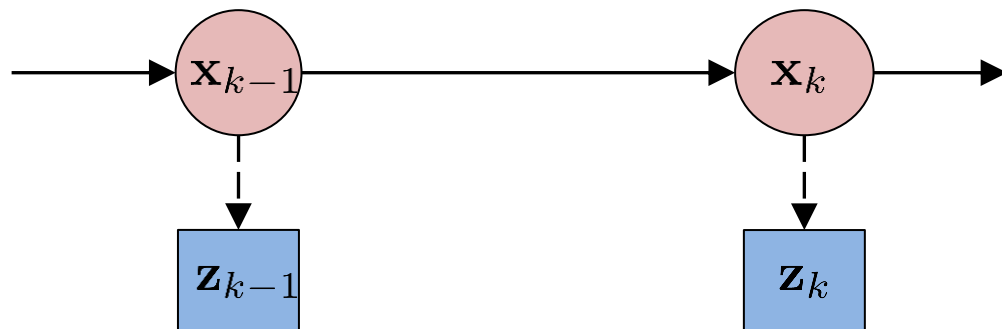


Importance of **Fault Detection** in GNSS/INS Integration and **assessment of Integrity**



Introduction

- Kalman filtering



- **Objectives:**

1. Exploit the residuals in GNSS/INS
2. Comparison between Innovation and Residual-based IM in single snapshot fault scenario
 - Distribution of Test
 - Minimum Detectable Bias
 - Protection Levels

Prediction:

$$\mathbf{x}_k^- = \mathbf{f}(\mathbf{x}_{k-1}^+)$$

$$\mathbf{P}_k^- = \Phi_k \mathbf{P}_{k-1}^+ \Phi_k^T + \mathbf{Q}_k$$

Update:

$$\mathbf{x}_k^+ = \mathbf{x}_k^- + \mathbf{K}_k (\mathbf{z}_k - \mathbf{h}(\mathbf{x}_k^-))$$

$$\mathbf{P}_k^+ = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^-$$

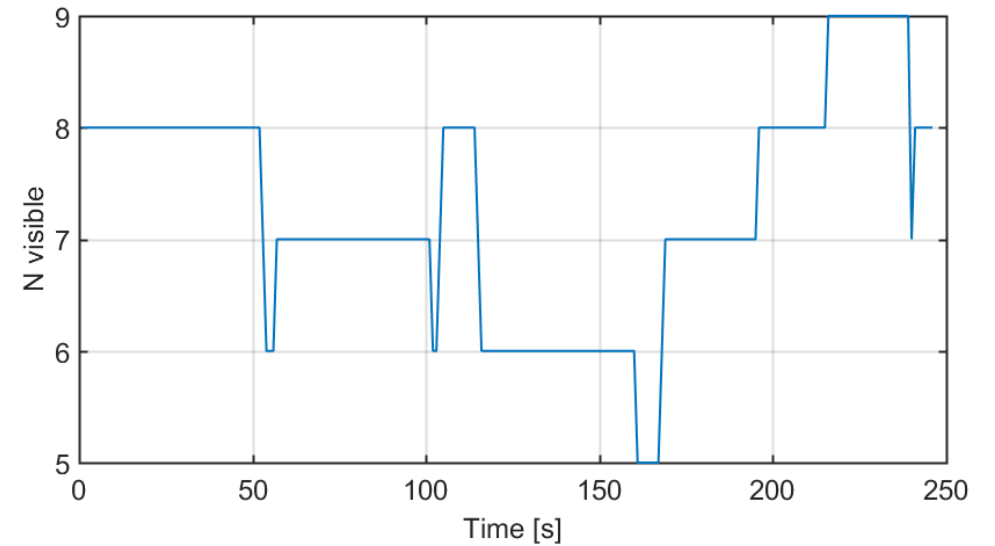
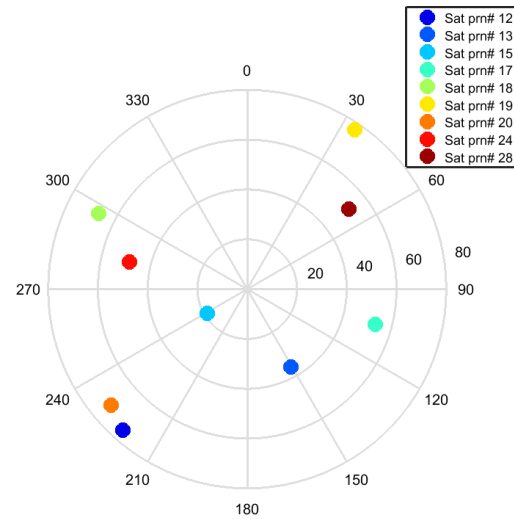
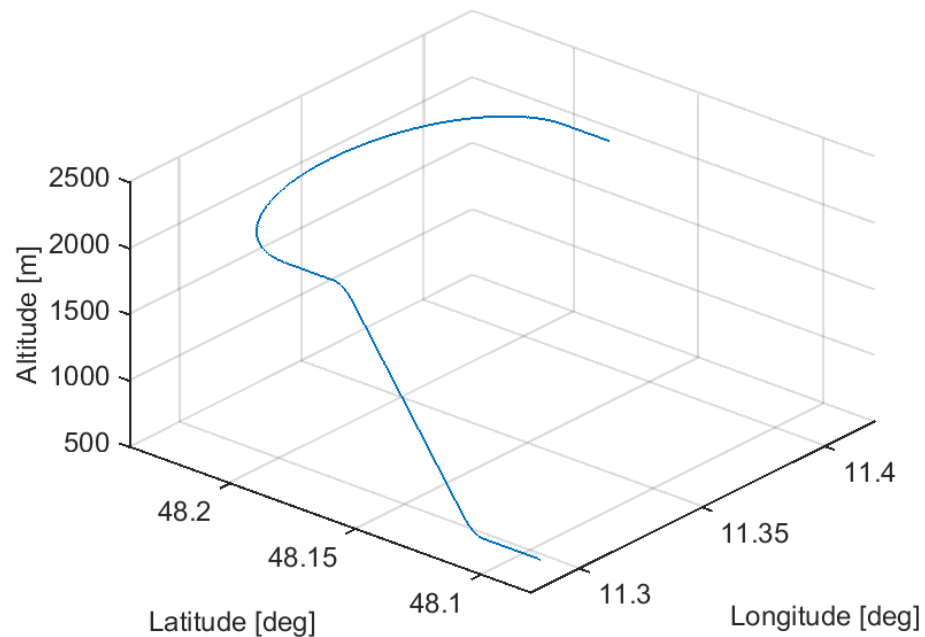
$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k)^{-1}$$

Innovation	Residual
$\gamma_k = \mathbf{z}_k - \mathbf{H}_k \mathbf{x}_k^-$	$\mathbf{r}_k = \mathbf{z}_k - \mathbf{H}_k \mathbf{x}_k^+$



Simulation Setup

- EKF with 17-states: $\mathbf{x}_{\text{EKF}} = \left(\delta\psi \quad \delta\mathbf{v} \quad \delta\mathbf{p} \quad \mathbf{b}_a \quad \mathbf{b}_g \quad \mathbf{b}_{\text{clk}} \right)^T$
- Tactical Grade IMU
- GPS code sigma = 5 m



Test Statistics

KF Innovation-based

- KF Innovation vector:

$$\boldsymbol{\gamma}_k = \mathbf{z}_k - \mathbf{H}_k \mathbf{x}_k^-$$

- Test Statistic:

$$q_{\gamma,k} = \boldsymbol{\gamma}_k^T \mathbf{S}_k^{-1} \boldsymbol{\gamma}_k$$

- Test statistic distribution:

- H0: $q_{\gamma,k} \sim \chi^2(0, n_k)$
- H1: $q_{\gamma,k} \sim \chi^2(\lambda^2, n_k)$

KF Residual-based

- KF residual vector:

$$\mathbf{r}_k = \mathbf{z}_k - \mathbf{H}_k \mathbf{x}_k^+$$

- Test Statistic:

$$q_{R,k} = \mathbf{r}_k^T \mathbf{R}_k^{-1} \mathbf{r}_k$$

- Test statistic distribution follows a Generalized Chi-Square*:

$$q_{R,k} = \sum_i^{p_B} \alpha_i^2 \chi_i^2$$

- CDF, PDF and Threshold computed numerically.

RAIM

- LS residuals:

$$\mathbf{r}_{LS,k} = \mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{x}}_{LS,k}$$

- Test Statistic:

$$q_{LS,k} = \mathbf{r}_{LS,k}^T \mathbf{R}_k^{-1} \mathbf{r}_{LS,k}$$

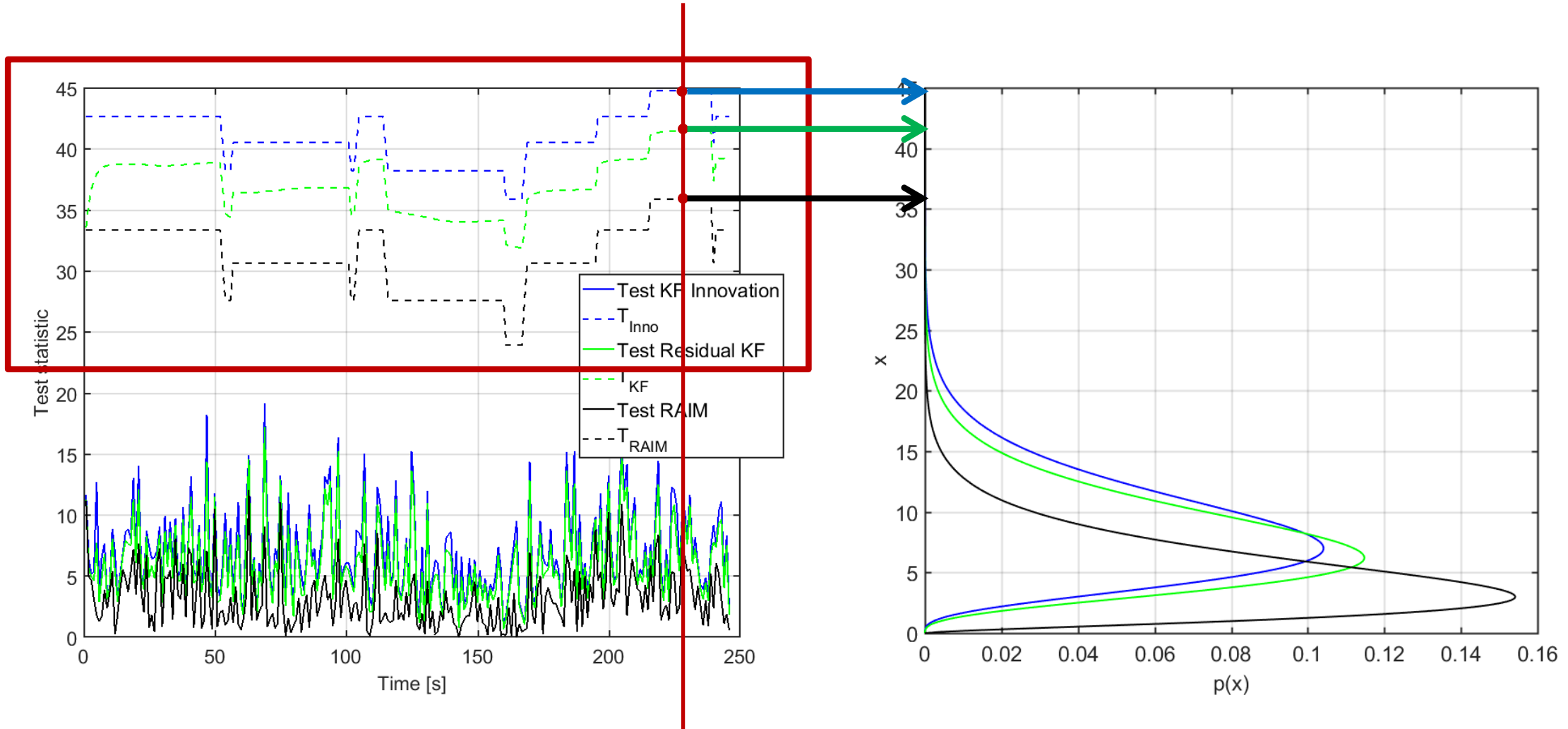
- Test statistic distribution:

- H0: $q_{LS,k} \sim \chi^2(0, n_k - 4)$
- H1: $q_{LS,k} \sim \chi^2(\lambda^2, n_k - 4)$

*M. Joerger and B. Pervan, "Kalman Filter-based Integrity Monitoring Against Sensor Faults," Journal of Guidance, Control, and Dynamics, vol. 36, no. 2, mar-apr 2013.



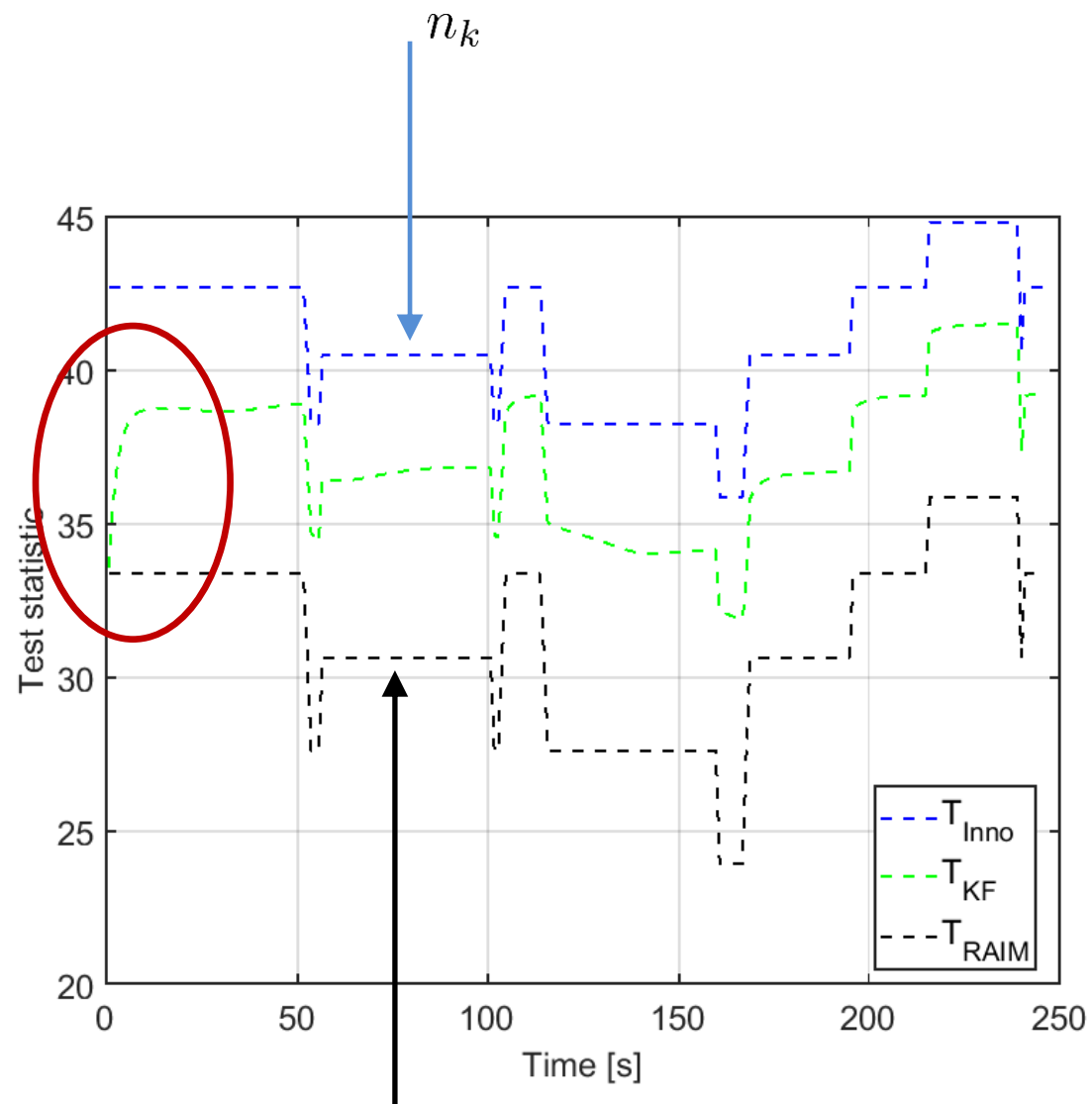
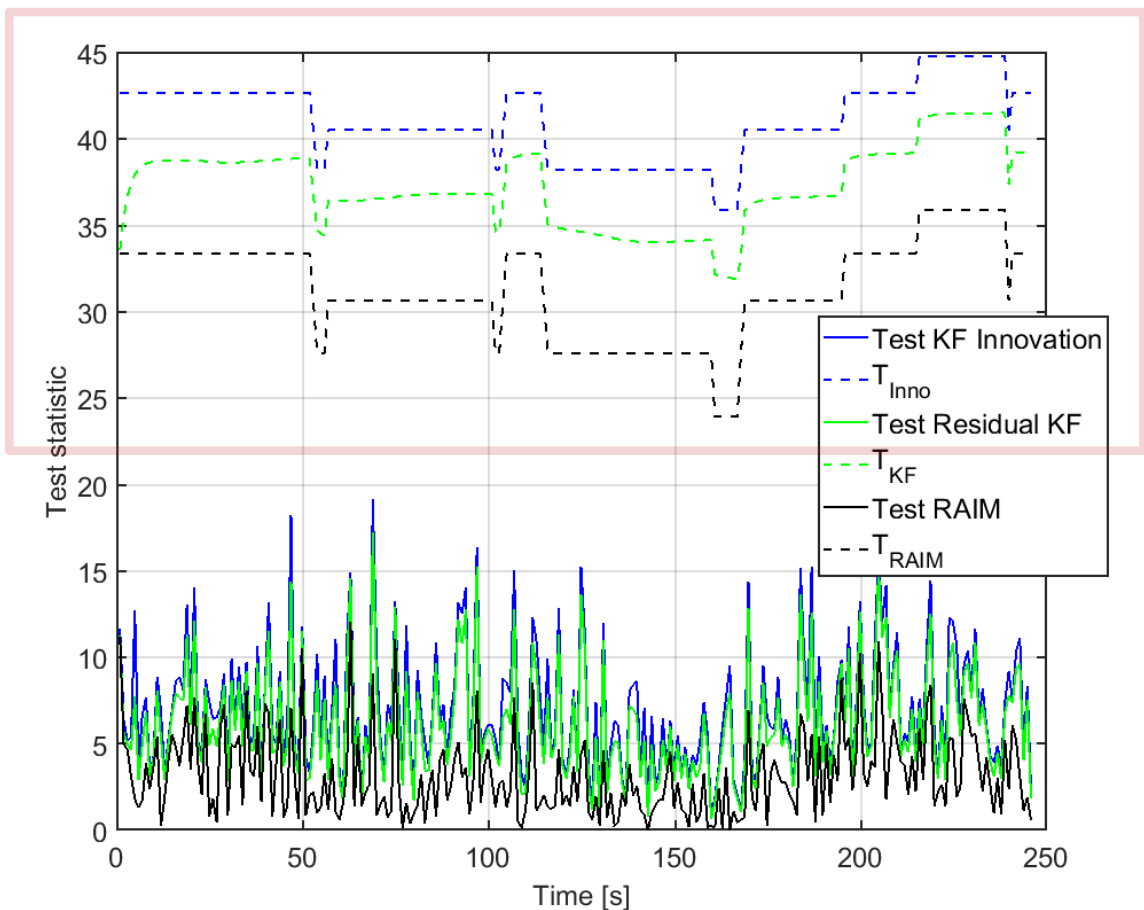
Evaluations: Test Statistics



$$P_{fa} = 1e^{-6}$$



Evaluations: Test Statistics



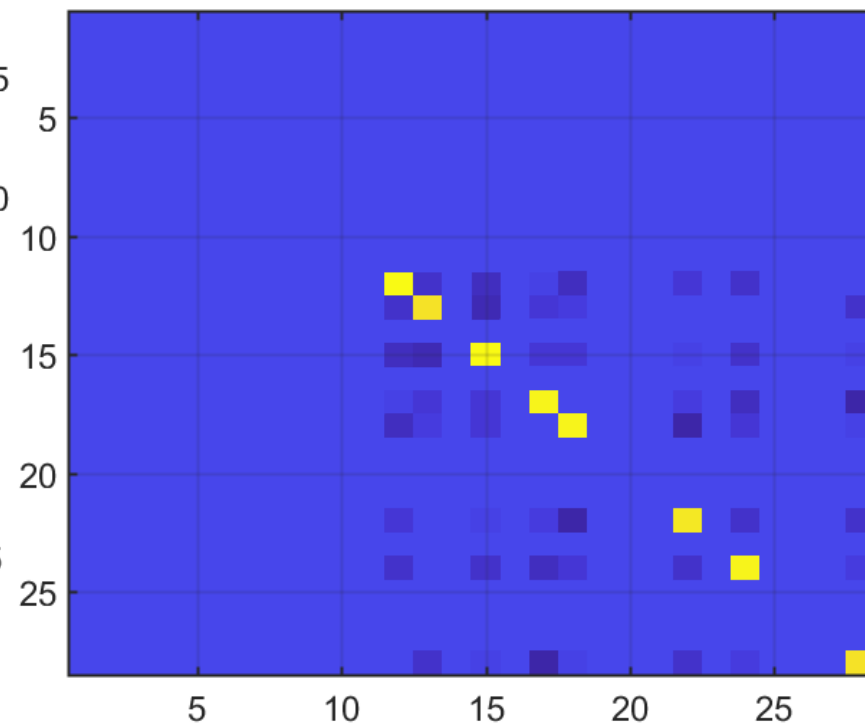
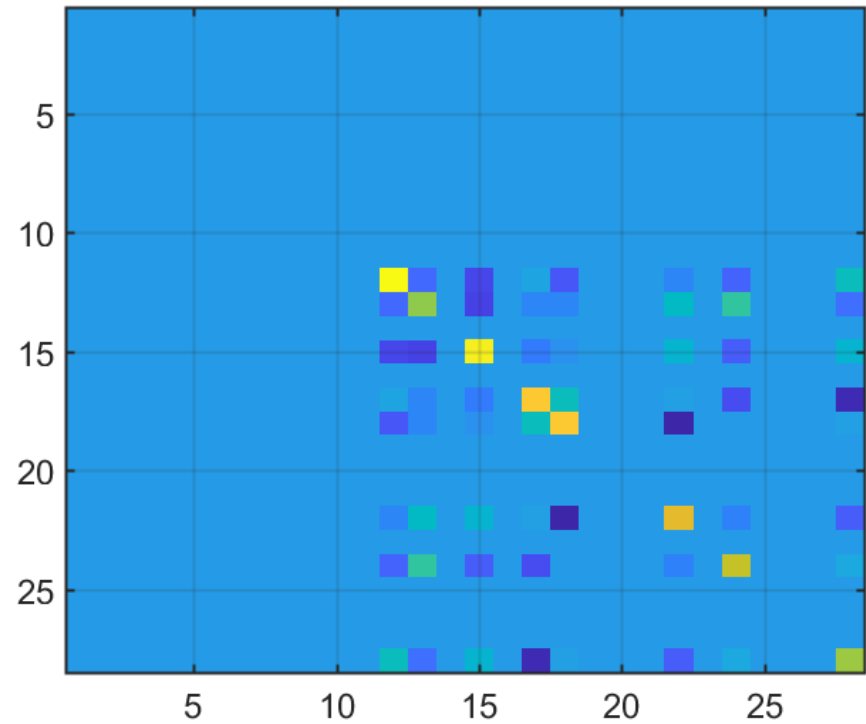
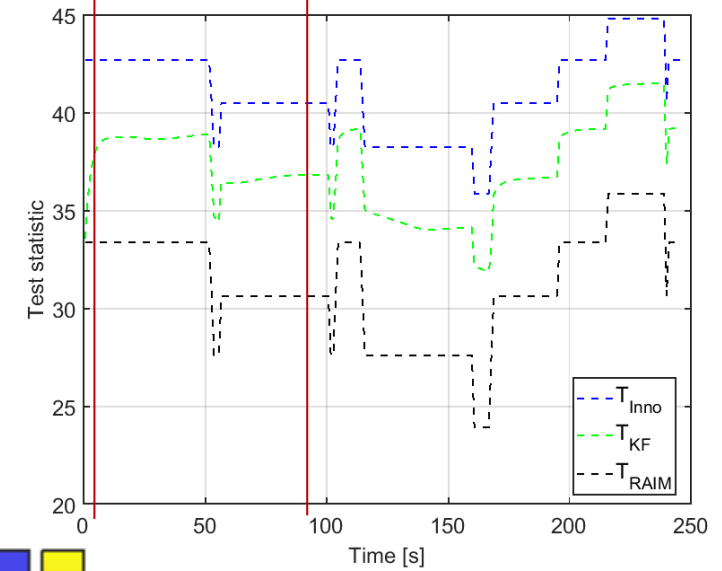
$$n_k - 4$$



Evaluations: Residuals Correlation

Converging phase

After Converge phase



Less Correlation



Less linear dependency



More degrees of freedom



Minimum Detectable Bias

- **Innovation-based:** $\gamma_k = (\mathbf{z}_k + \mathbf{f}_k) - \mathbf{H}_k \mathbf{x}_k^-$
- Minimum Detectable Bias (MDB):

$$MDB_i = \frac{\lambda_0}{\sqrt{\mathbf{e}_i^T \mathbf{S}^{-1} \mathbf{e}_i}}$$

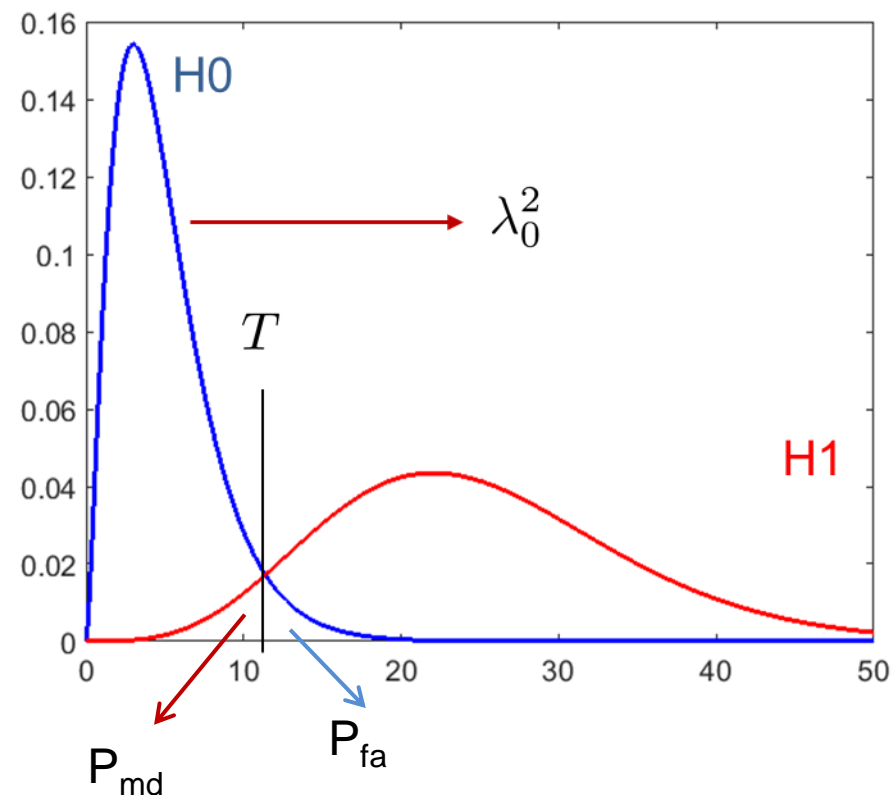
- **Residual-based:**

$$q_{R,k} = \sum_i^{p_B} \alpha_i^2 y_i^2$$

$$\mathbf{B} = \mathbf{R}_k^{-1/2} \mathbf{P}_{r,k}^{-1/2} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^T$$

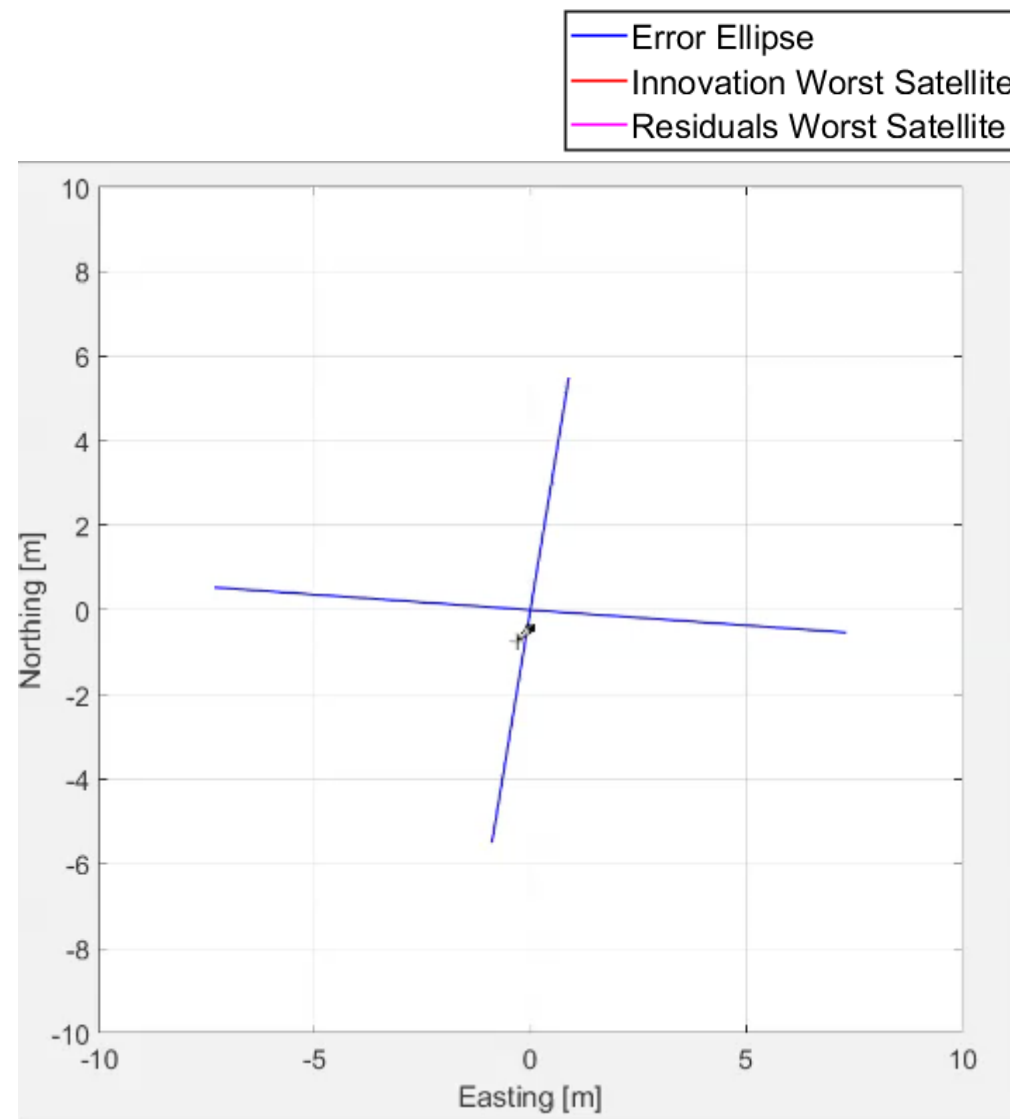
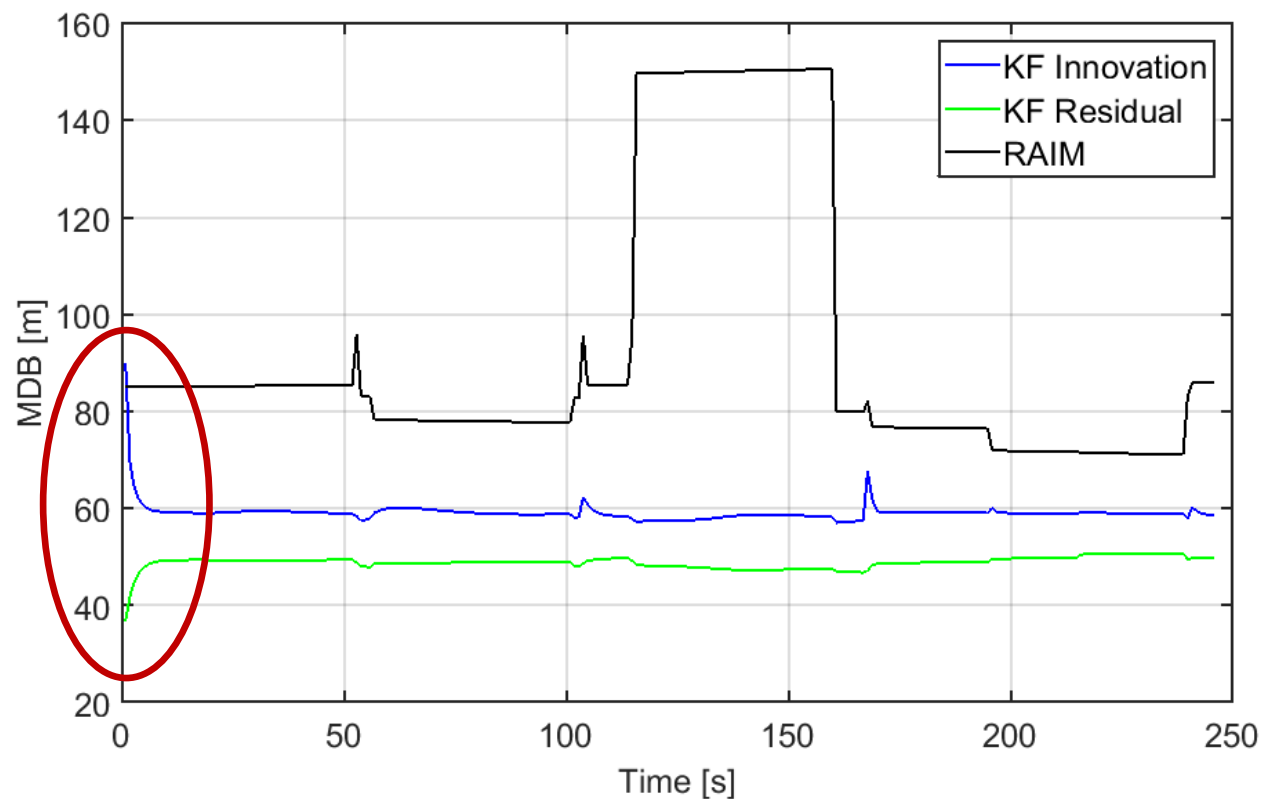
$$y_i \sim \mathcal{N} \left(\alpha_i^{-1} \mathbf{T}_i^T \mathbf{V}^T \mathbf{P}_{r,k}^{-1/2} E[\mathbf{r}_k], 1 \right)$$

$$E[\mathbf{r}_k] = (\mathbf{I} - \mathbf{H}_k \mathbf{K}_k) \underbrace{\mathbf{e}_i}_{\mathbf{f}_i} MDB_i$$



$$\hat{M}DB_i = \min_{\mu_i(MDB_i)} \left\| P_{md} - [Pr(q_{R,k}(p_B, \alpha, \mu_i) \leq T_{R,k})] \right\|^2$$

Evaluations: Minimum Detectable Bias



Protection levels

$$VPL = V slope_{max} \sqrt{T(P_{fa})} + K_v \sqrt{P_{uu}}.$$

- Innovation based:

$$V slope_{\gamma,k,i} = \sqrt{\frac{\mathbf{e}_i^T \mathbf{K}_k^T \boldsymbol{\epsilon}_v^T \boldsymbol{\epsilon}_v \mathbf{K}_k \mathbf{e}_i}{\mathbf{e}_i^T \mathbf{S}_k^{-1} \mathbf{e}_i}}$$

← Bias propagation to Error

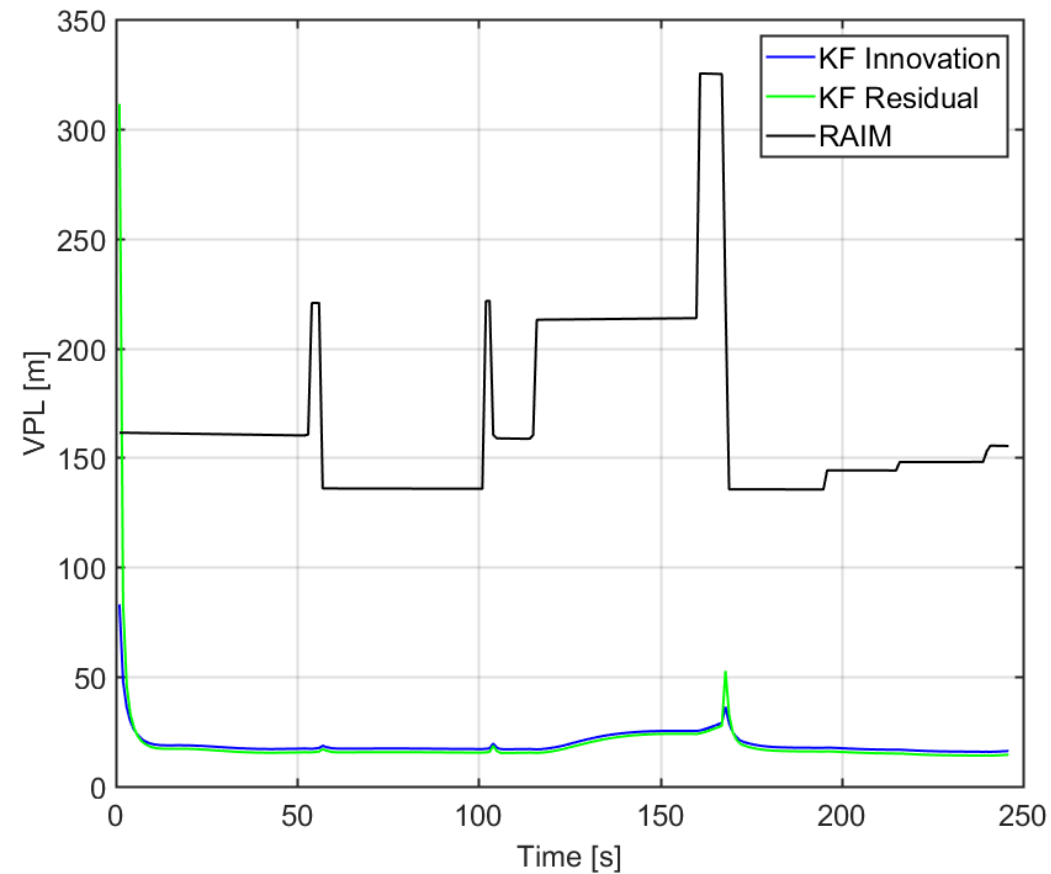
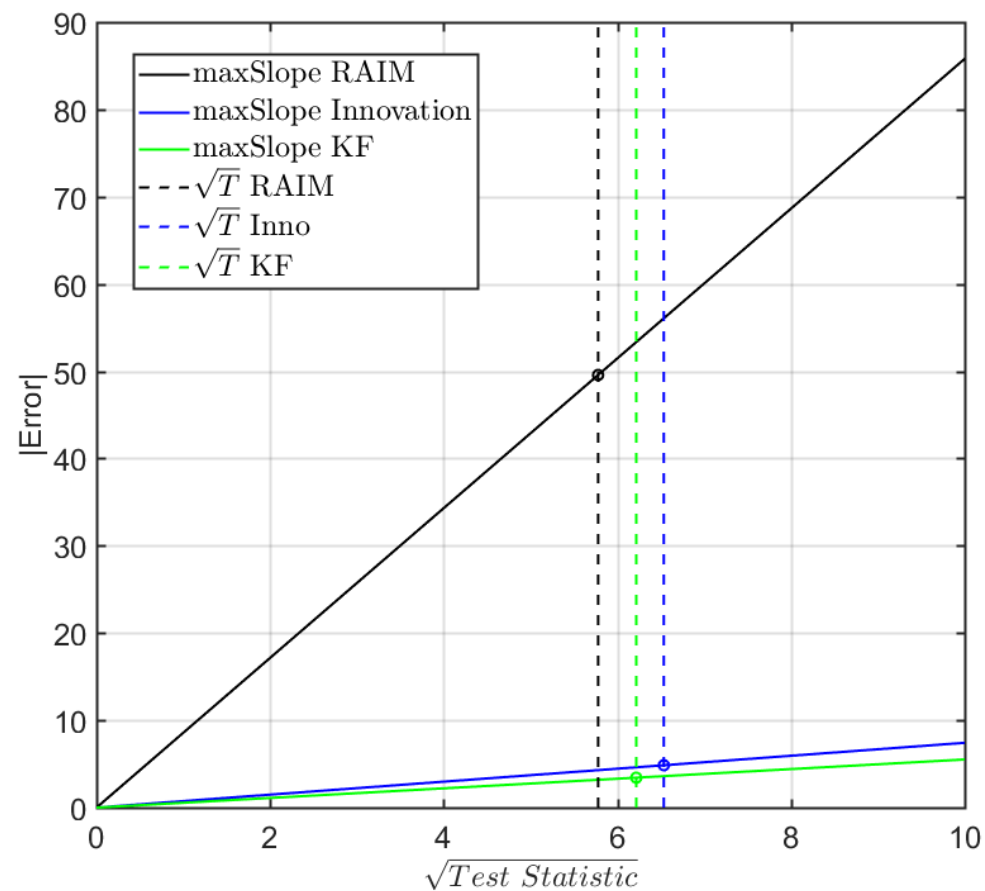
← Bias propagation to non-central parameter

- Residual based:

$$V slope_{R,k,i} = \sqrt{\frac{\mathbf{e}_i^T \mathbf{K}_k^T \boldsymbol{\epsilon}_v^T \boldsymbol{\epsilon}_v \mathbf{K}_k \mathbf{e}_i}{\sum_j^{p_B} \left(\mathbf{T}_j^T \mathbf{V}^T \mathbf{P}_{r,k}^{-1/2} (\mathbf{I} - \mathbf{H}_k \mathbf{K}_k) \mathbf{e}_{i,k} \right)^2}}$$

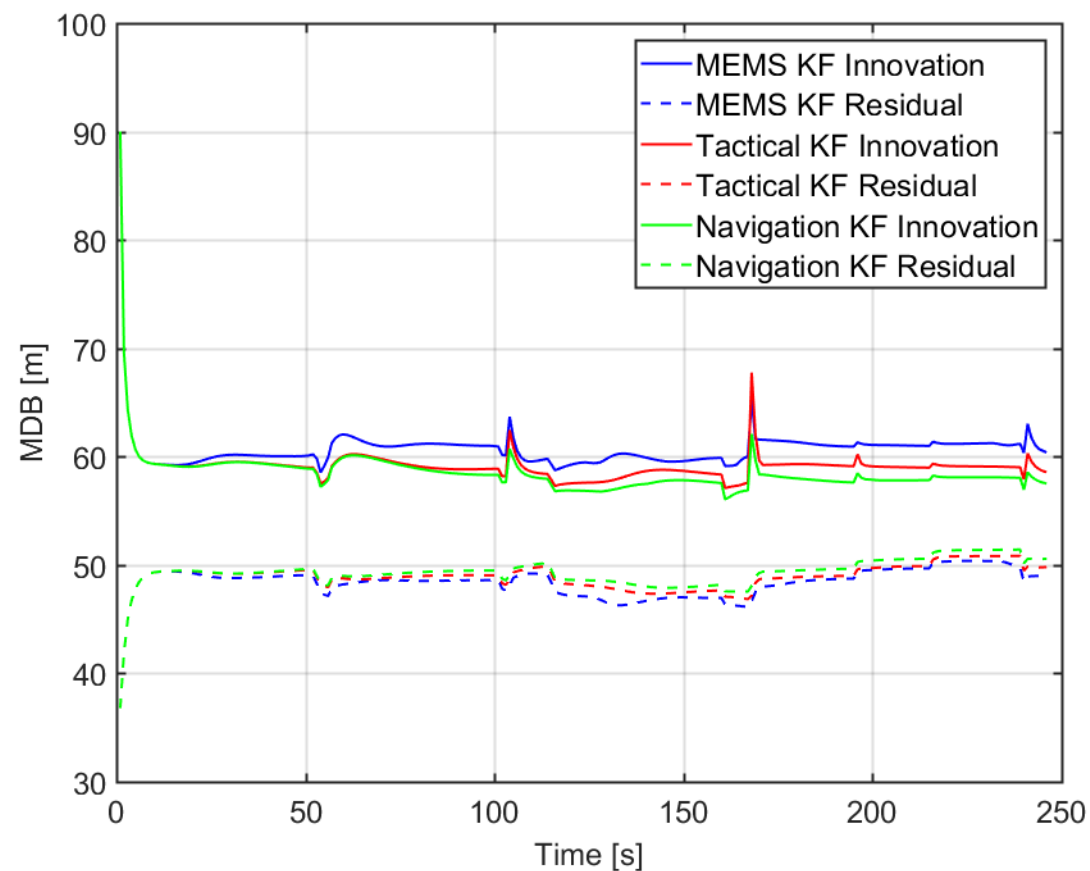
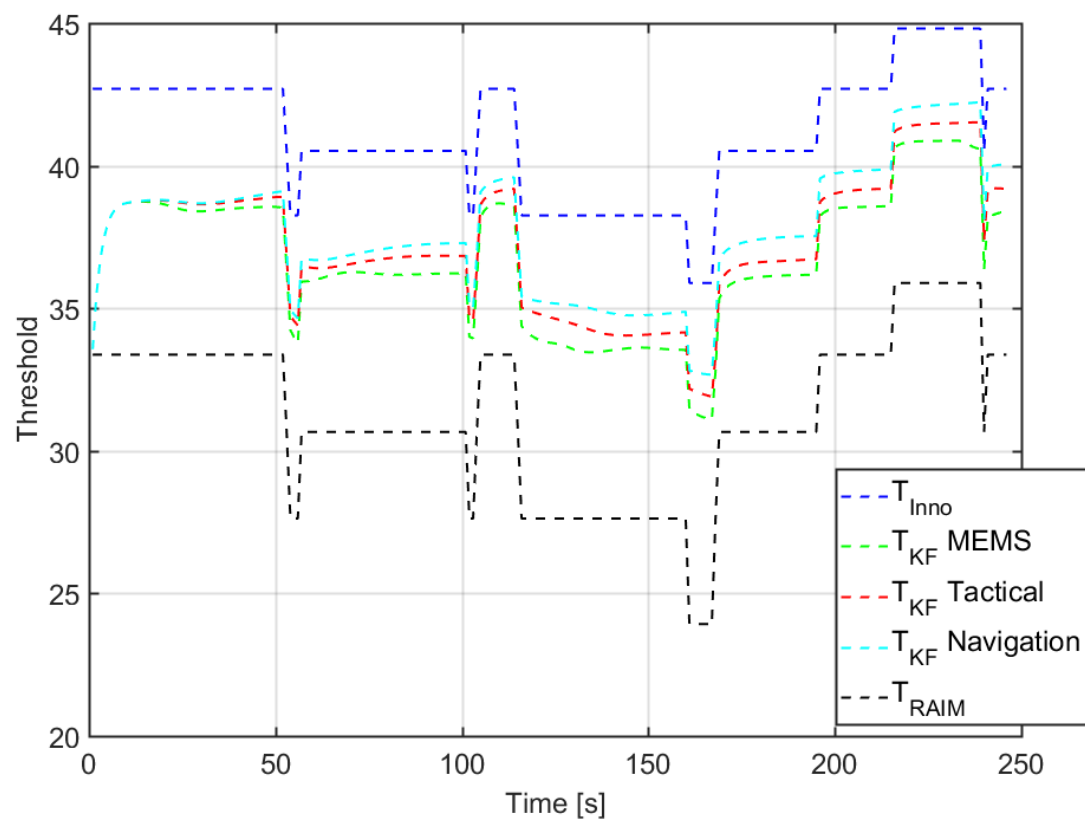


Evaluations: Slopes & VPL

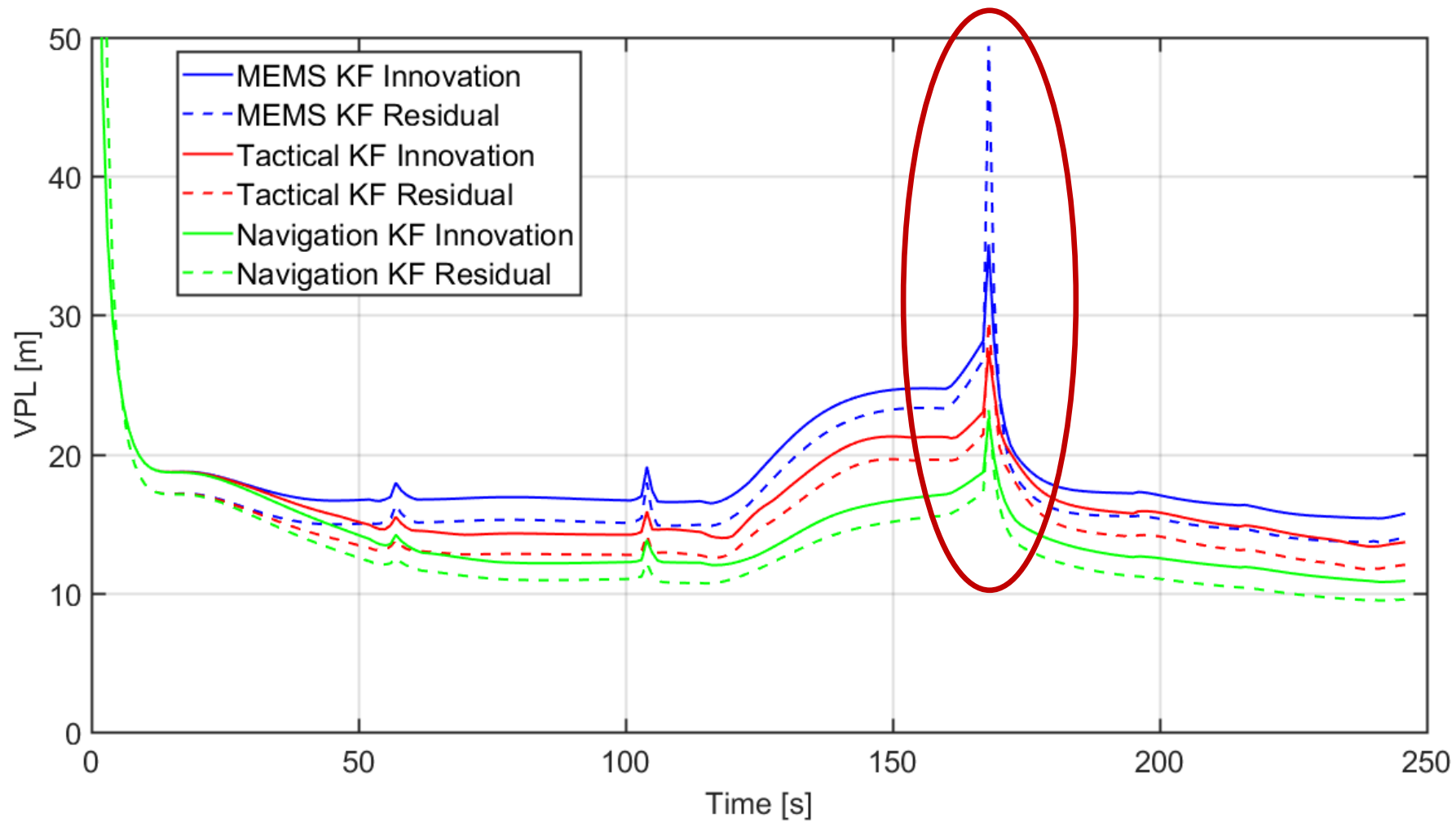


Evaluations: Inertial Quality Influence

	Accelerometer			Gyroscope		
	Noise [$\mu\text{g}/\sqrt{\text{Hz}}$]	Bias Noise [μg]	τ [s]	Noise [$\text{deg}/\text{h}/\sqrt{\text{Hz}}$]	Bias Noise [deg/h]	τ [s]
Navigation	15	20	3000	0.01	0.005	10000
Tactical	50	160	3000	2	0.5	10800
MEMS	120	150	25	10	15	600



Evaluations: Inertial Quality Influence (VPL)



Conclusions & Outlook

- Distribution of residual-based test is modulated by the prediction uncertainty $n_k - 4 < dof_R < n_k$
- Threshold and other statistics must be computed numerically at each time
- Residuals and innovation show complementary behaviors in Fault Detection
- In the single fault case, residual-based shows better performance than innovation one in general

- Will look at sequential faults and multiple faults

Thank you

