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都市部におけるGNSS単独測位性能改善に関する研究

2019/02/15　情報通信工学研究室 冨永貴樹

Background and progress

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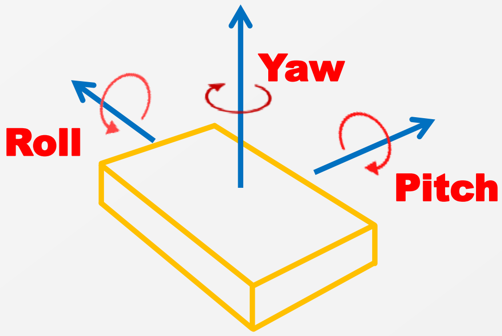
- **High demand for precise and robust GNSS navigation in the automotive market.**
  - applications such as Autonomous Driving, ADAS, and V2X.
- **GNSS SPP (Single Point Positioning) is still important for the "robust" navigation.**
  - PPP/RTK lost compensation
  - Sensor calibration



Background and progress

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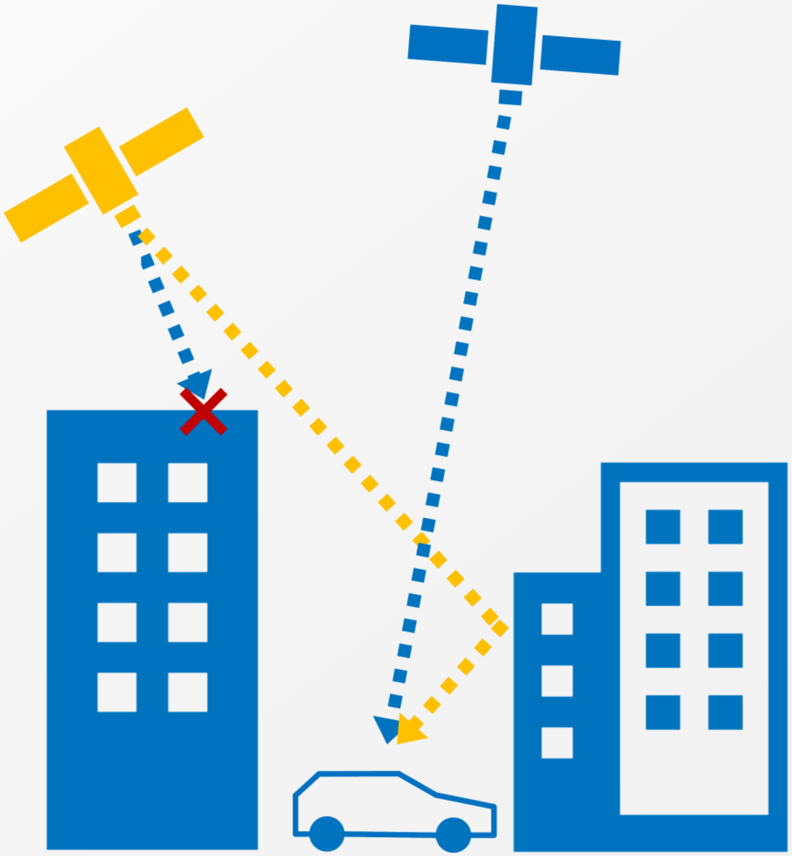
- **Implemented adaptive EKF to improve the GNSS SPP performance of a mass product receiver in an urban environment.**
  - **Performance : accuracy and precision, and its integrity.**
  - **This is the challenge in the urban canyon because of NLOS (Non-Line-Of-Sight) signal tracking.**



Agenda

- Introduction to Adaptive Kalman Filter
  – Kalman filter
  – IAE(Innovation-based Adaptive Estimation)
  – Applying IAE to GNSS

- Adaptive EKF vs. Urban Canyon
  – Positioning accuracy and precision
  – Measurement error and predicted sigma
  – Integrity Information

- Conclusion and future works

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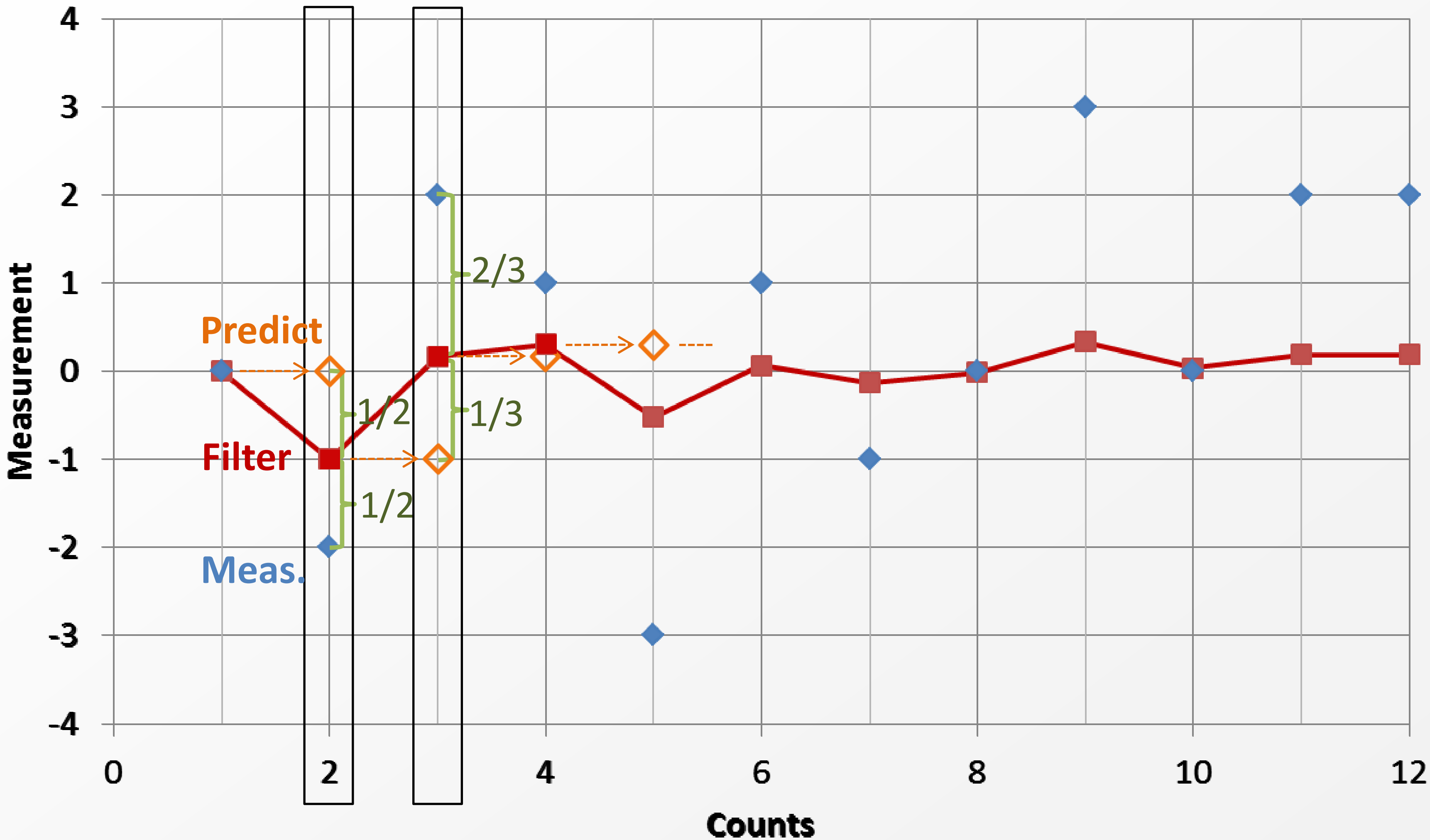
Hatch filter

$$x_k = \frac{1}{M} z_k + \frac{M-1}{M} x_{\bar{k}}$$



Weighted-LS-based filter

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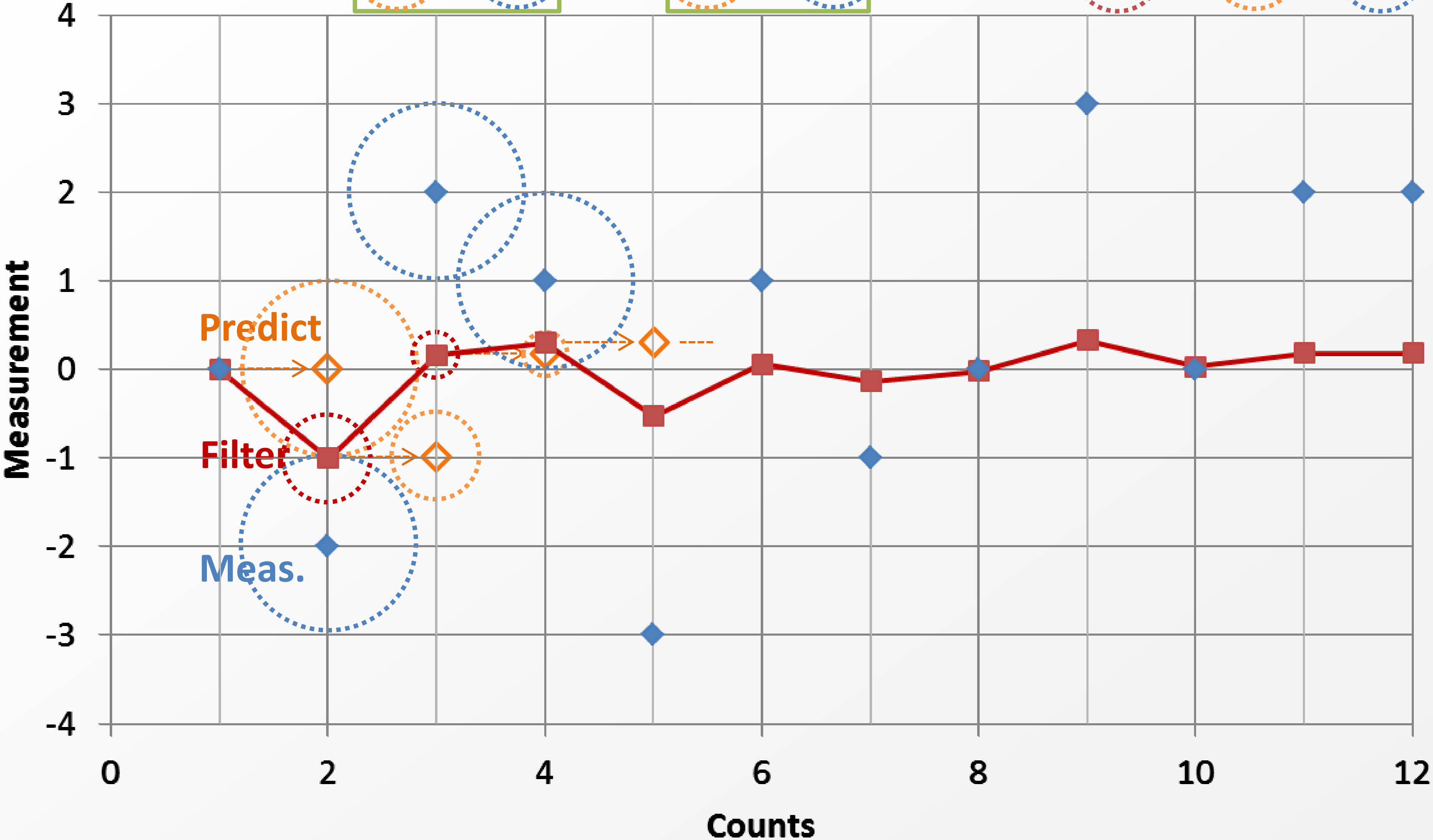
$$x_k = \frac{\sigma_{x_{\bar{k}}}^2}{\sigma_{x_{\bar{k}}}^2 + \sigma_{z_k}^2} z_k + \frac{\sigma_{z_k}^2}{\sigma_{x_{\bar{k}}}^2 + \sigma_{z_k}^2} x_{\bar{k}}$$

$$\frac{1}{\sigma_{x_k}^2} = \frac{1}{\sigma_{x_{\bar{k}}}^2} + \frac{1}{\sigma_{z_k}^2}$$



Kalman filter

- **Weighted-LS:**

$$x_k = \frac{\sigma_{x_{\bar{k}}}^2}{\sigma_{x_{\bar{k}}}^2 + \sigma_{z_k}^2} z_k + \frac{\sigma_{z_k}^2}{\sigma_{x_{\bar{k}}}^2 + \sigma_{z_k}^2} x_{\bar{k}}$$

$$\sigma_{x_k}^2 = \frac{\sigma_{z_k}^2 \sigma_{x_{\bar{k}}}^2}{\sigma_{x_{\bar{k}}}^2 + \sigma_{z_k}^2}$$

- **Defining:**

$$K_k = \frac{\sigma_{x_{\bar{k}}}^2}{\sigma_{z_k}^2 + \sigma_{x_{\bar{k}}}^2}$$

- **Then,**

$$x_k = x_{\bar{k}} + K_k (z_k - x_{\bar{k}})$$

$$\sigma_{x_k}^2 = (1 - K_k)\sigma_{x_{\bar{k}}}^2$$

Measurement Update

- **And,**

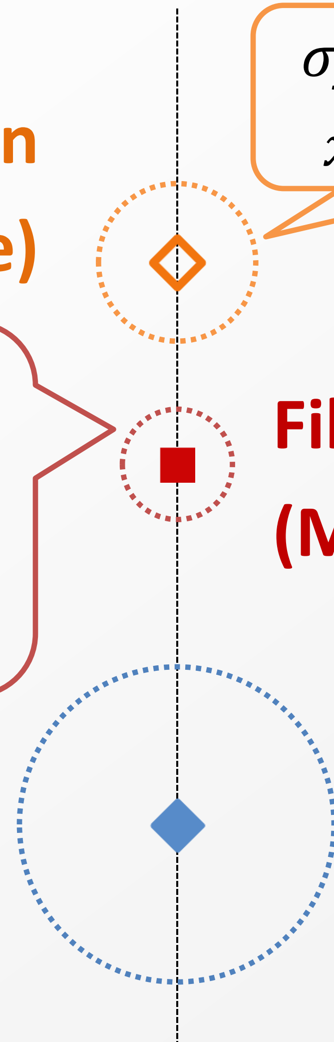
$$\sigma_{x_{\bar{k}}}^2 = \sigma_{x_{k-1}}^2 + \sigma_{\varepsilon}^2$$

$$x_{\bar{k}} = x_{k-1} + v_k$$

Time Update

Kalman filter

- **Summary for Kalman filter**



Prediction (Time update)

$$\sigma^2_{x_{\bar{k}}} = \sigma^2_{x_{k-1}} + \sigma^2_{\varepsilon}$$

$$x_{\bar{k}} = x_{k-1} + v_k$$

Filter (Measurement Update)

$$K_k = \frac{\sigma^2_{x_{\bar{k}}}}{\sigma^2_{x_{\bar{k}}} + \sigma^2_{z_k}}$$

$$x_k = x_{\bar{k}} + K_k (z_k - x_{\bar{k}})$$

$$\sigma^2_{x_k} = (1 - K_k)\sigma^2_{x_{\bar{k}}}$$

Measurement

$$\sigma^2_{z_k}$$

$$z_k$$

epoch k

Extended-Kalman filter(EKF)

- Non-linear system

$$z = h(x) + \varepsilon$$

  - By Taylor series,

$$h(x) = h(x_0) + H(x - x_0) + \cdots$$

$$H = \left.\frac{\partial h(x)}{\partial x}\right|_{x=x_0}$$

  - Linearize : $z \sim h(x_0) + H(x - x_0) + \varepsilon$

$$x = x_0 + H^{-1}\big(z - h(x_0)\big) + \varepsilon$$

- EKF formulation,

$$x_k = x_{\bar{k}} + K_k\big(z - h(x_{\bar{k}})\big)$$

$$\left(\lim_{R_k \to 0} K_k = H^{-1}\right)$$

Extended-Kalman filter(EKF)

- **Summary**

Predictiton (Time update)

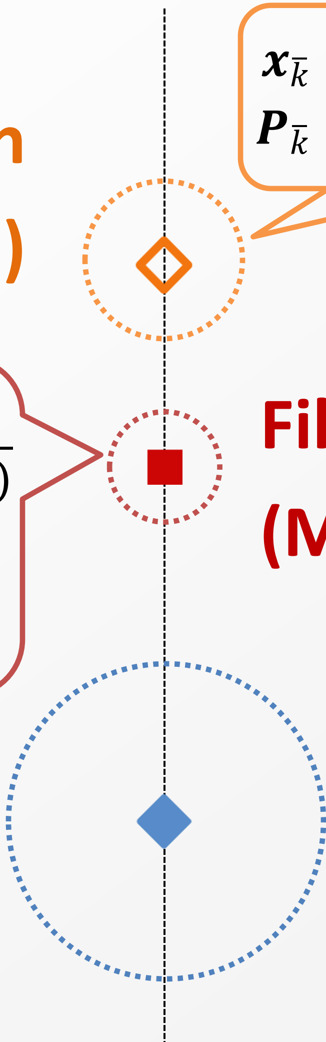
$$\boldsymbol{x}_{\bar{k}} = \boldsymbol{F}_k \boldsymbol{x}_{k-1} + \boldsymbol{D}_k \boldsymbol{u}_k$$
$$\boldsymbol{P}_{\bar{k}} = \boldsymbol{F}_k \boldsymbol{P}_{k-1} \boldsymbol{F}_{k-1}^T + \boldsymbol{Q}_k$$

Filter (Measurement Update)

$$\boldsymbol{K}_k = \frac{\boldsymbol{P}_{\bar{k}} \boldsymbol{H}(\boldsymbol{x}_{\bar{k}})^T}{\left(\boldsymbol{H}(\boldsymbol{x}_{\bar{k}}) \boldsymbol{P}_{\bar{k}} \boldsymbol{H}(\boldsymbol{x}_{\bar{k}})^T + \boldsymbol{R}_k\right)}$$
$$\boldsymbol{x}_k = \boldsymbol{x}_{\bar{k}} + \boldsymbol{K}_k\left(\boldsymbol{z}_k - \boldsymbol{h}(\boldsymbol{x}_{\bar{k}})\right)$$
$$\boldsymbol{P}_k = \left(\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}(\boldsymbol{x}_{\bar{k}})\right) \boldsymbol{P}_{\bar{k}}$$

Measurement

$$\boldsymbol{z}_k \quad \boldsymbol{R}_k$$



epoch k

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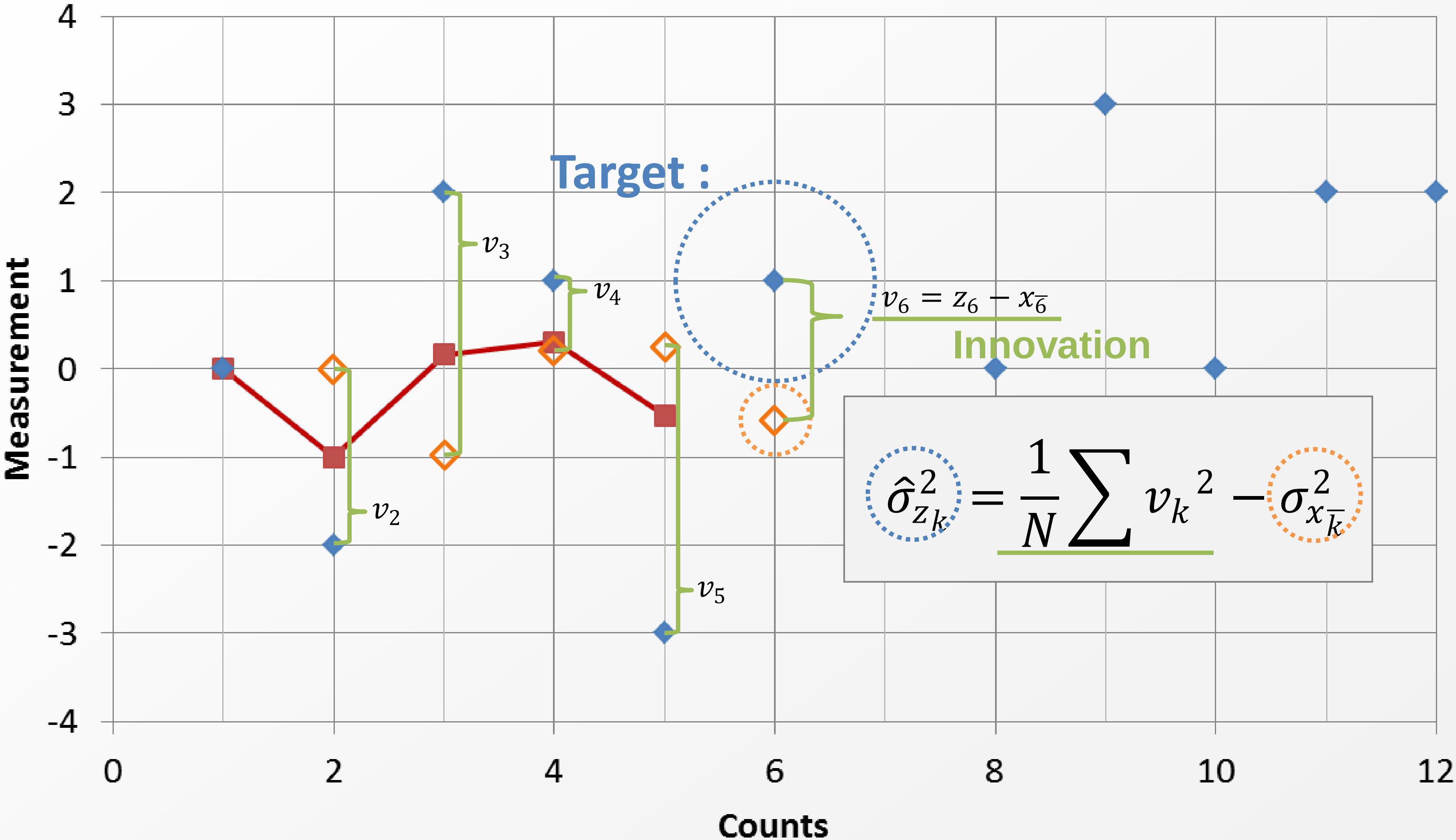
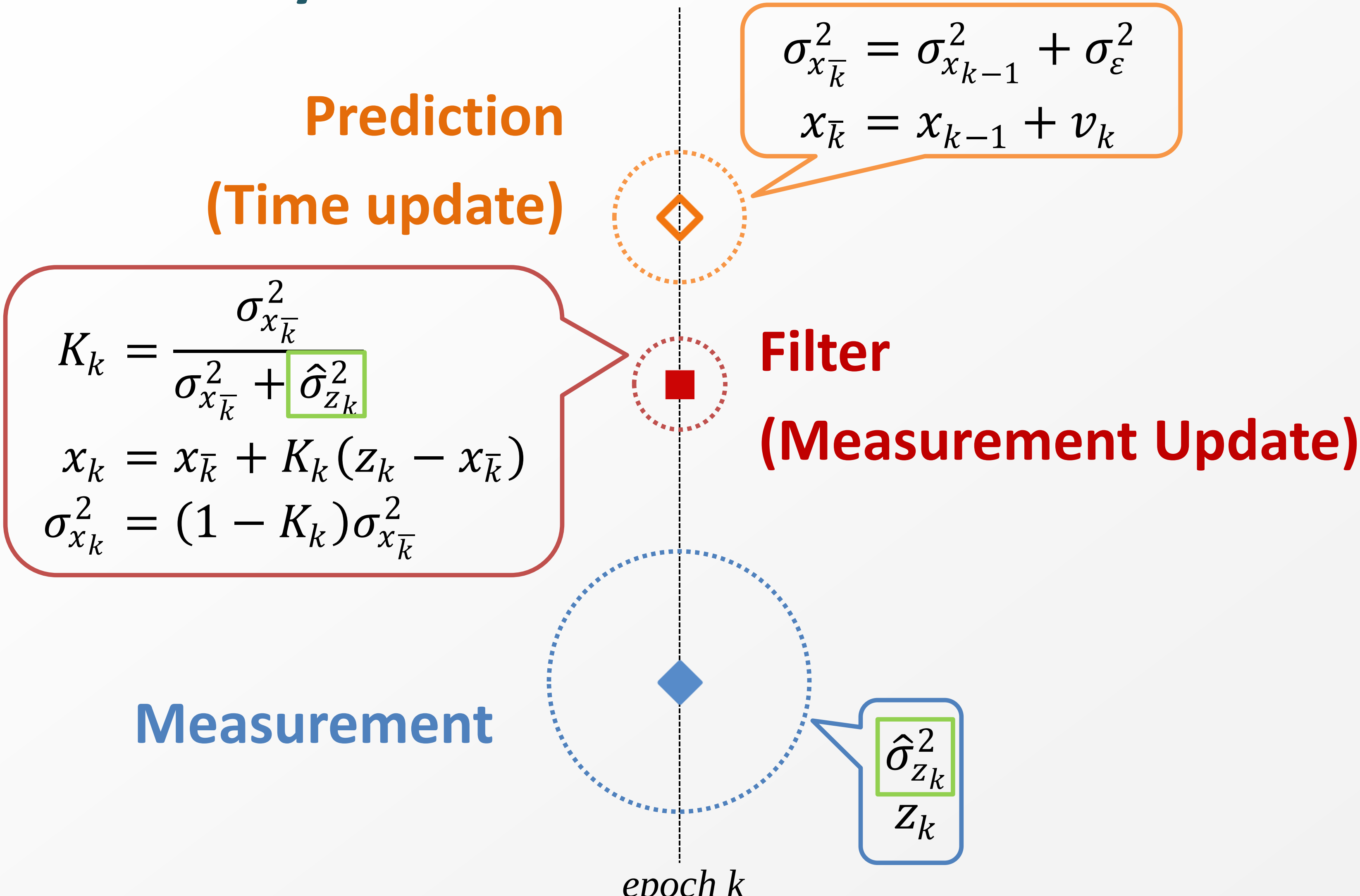
IAE(Innovation-based Adaptive Estimation)

- **Run KF with appropriate $\sigma_{z_k}^2$, which is <u>unknown</u>.**



Kalman filter

- **Summary for IAE**



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Applying IAE to Outlier

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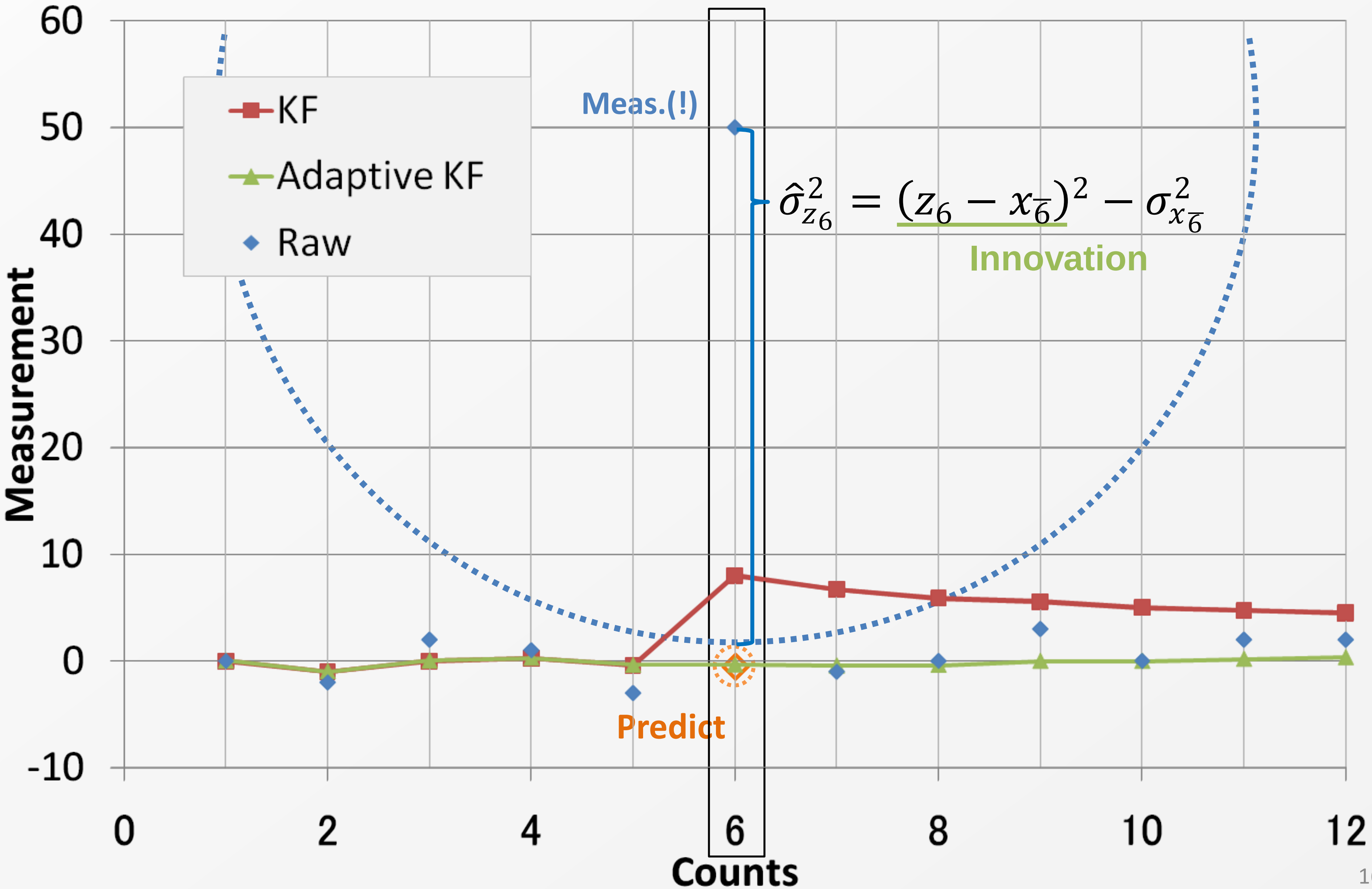
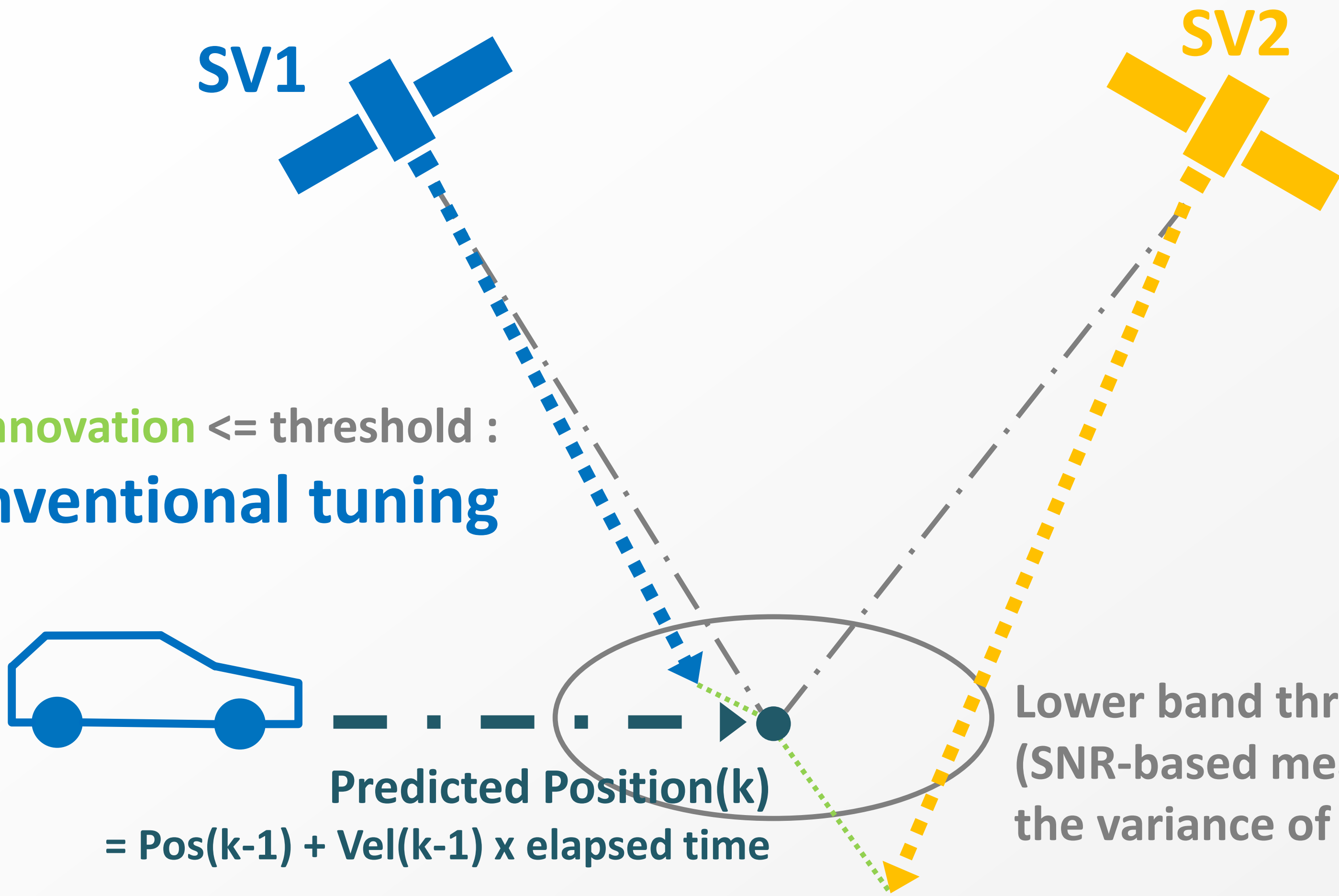


Applying IAE to GNSS



Innovation <= threshold :

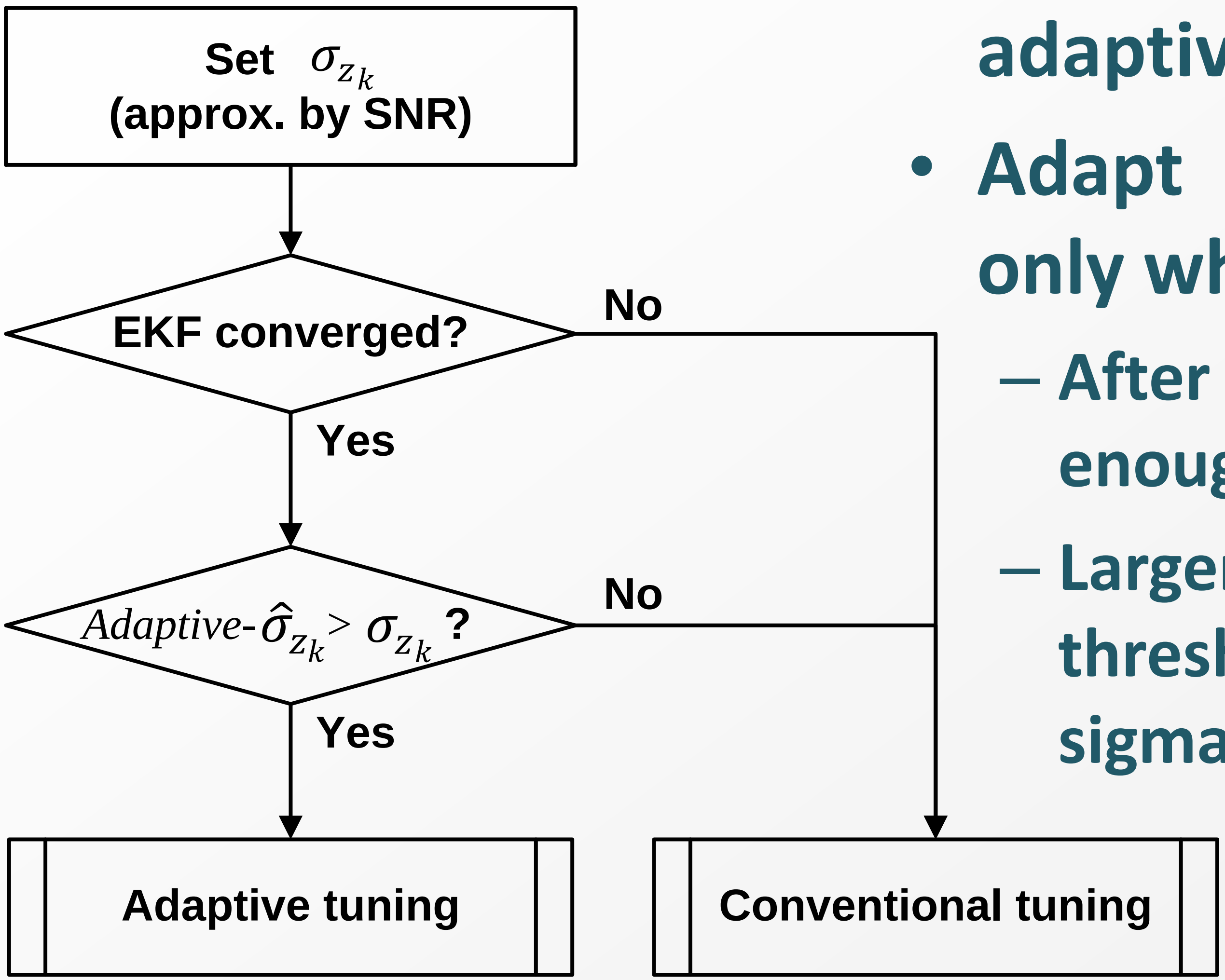
Conventional tuning

Lower band threshold
(SNR-based meas. variance +
the variance of prediction)

Innovation > threshold :

Adaptive tuning

Applying IAE to GNSS



- Process flow to create adaptive $\boldsymbol{R}_k$.
- Adapt the innovation only when:
  - After EKF converged enough.
  - Larger than lower band threshold (SNR-based sigma).

Applying IAE to GNSS

- **Summary for extended-Kalman filter (EKF)**

Prediction (Time update)

$$x_{\bar{k}} = F_k x_{k-1} + D_k u_k$$
$$P_{\bar{k}} = F_k P_{k-1} F_{k-1}^T + Q_k$$

Filter (Measurement Update)

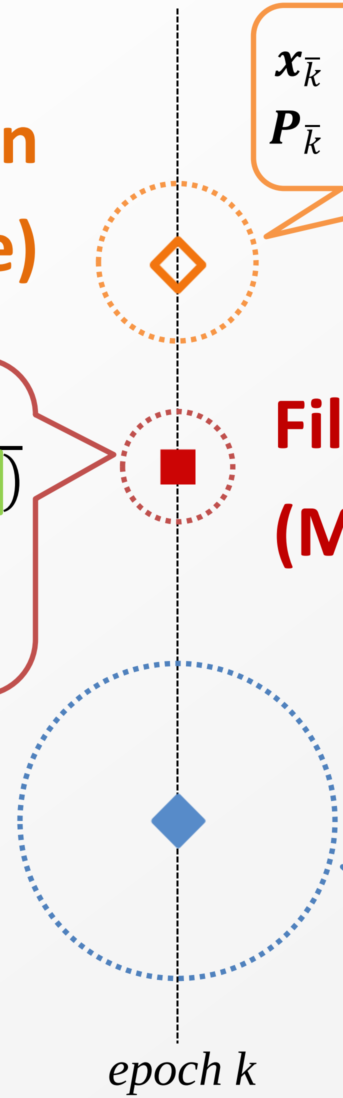
$$K_k = \frac{P_{\bar{k}} H(x_{\bar{k}})^T}{\left(H(x_{\bar{k}}) P_{\bar{k}} H(x_{\bar{k}})^T + \hat{R}_k\right)}$$
$$x_k = x_{\bar{k}} + K_k\left(z_k - h(x_{\bar{k}})\right)$$
$$P_k = \left(I - K_k H(x_{\bar{k}})\right) P_{\bar{k}}$$

Measurement

z_k

$\hat{R}_k$

Adaptive covariance matrix of measurement noise



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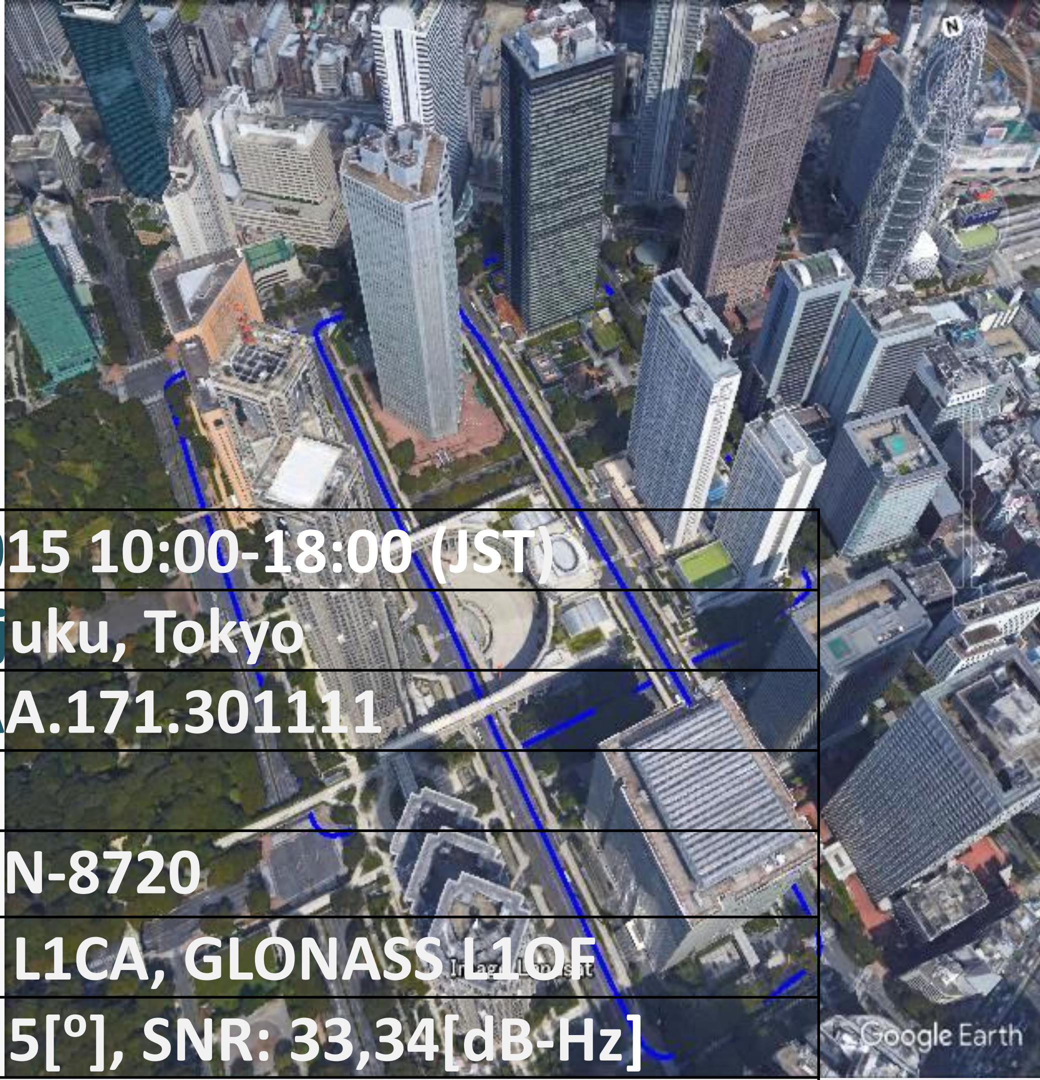
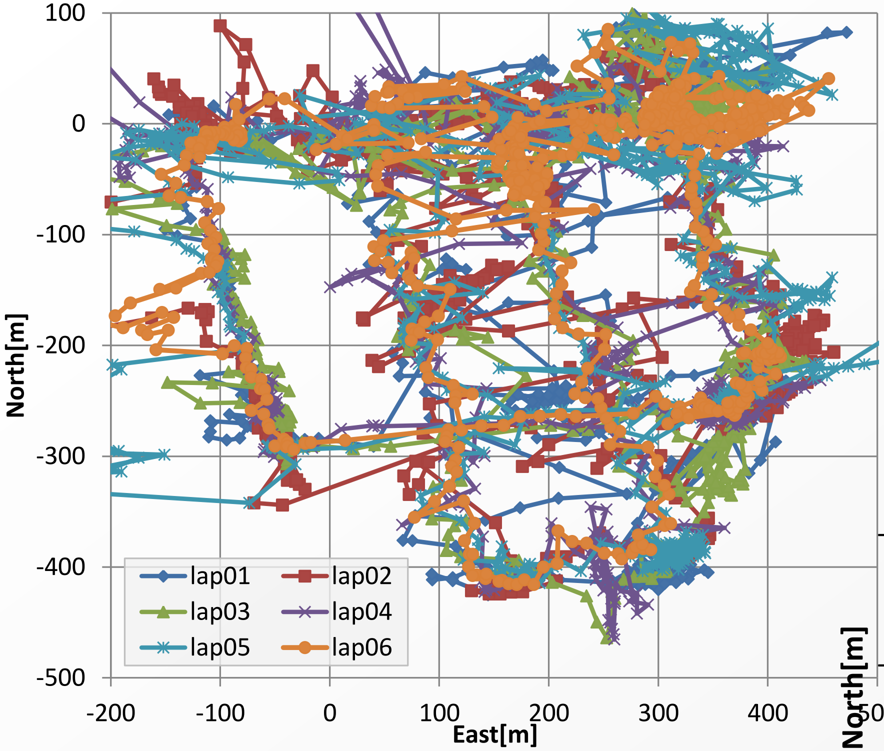
Urban Challenge



- **Test configurations**

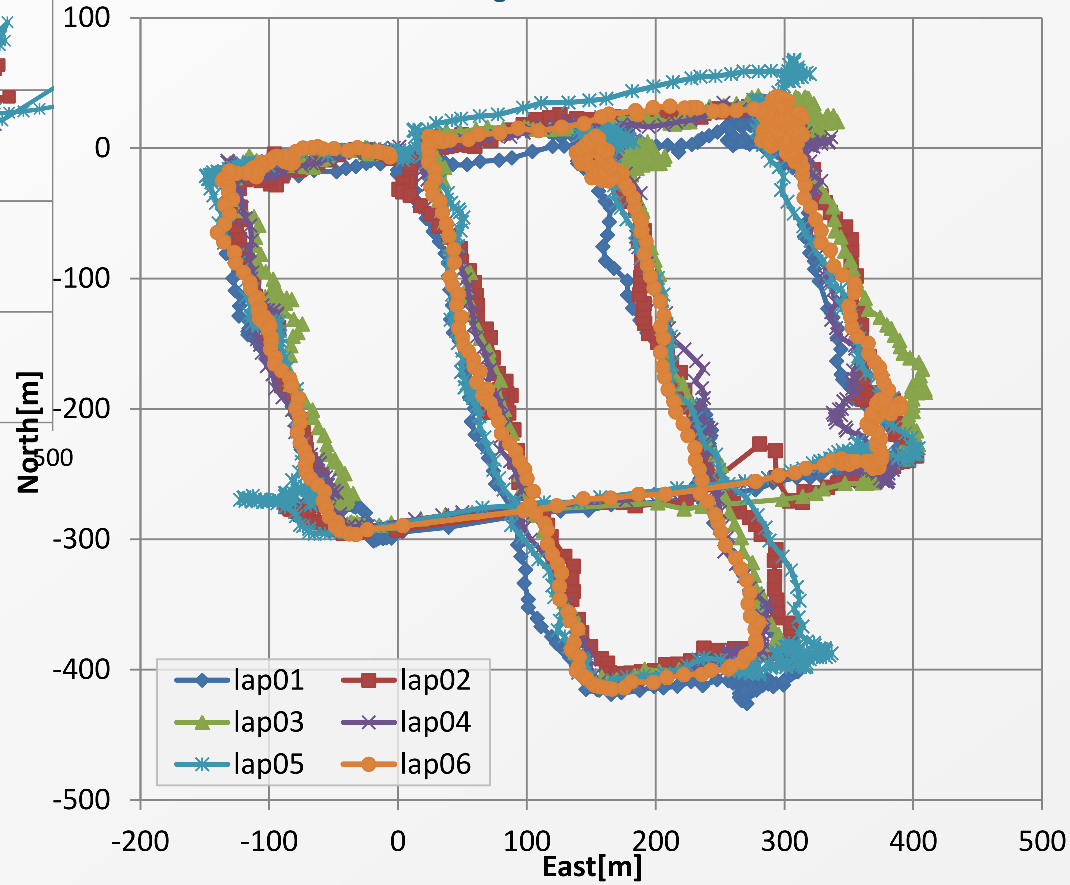
Date & Time	Nov.9th .2015 10:00-18:00 (JST)
Test Area	Nishi-shinjuku, Tokyo
Antenna Type	Taoglas AA.171.301111
Antenna Place	Car roof
Raw Meas.	Furuno GN-8720
GNSS System	GPS/QZSS L1CA, GLONASS L1OF
Masks	Elevation: 5[°], SNR: 33,34[dB-Hz]
Sampling Rate	1Hz
True Position	Applanix POSLV 520(Post Proc.)
EKF Types	Conventional EKF & Adaptive EKF

Horizontal position error



Conventional EKF

Adaptive EKF



Vertical position error

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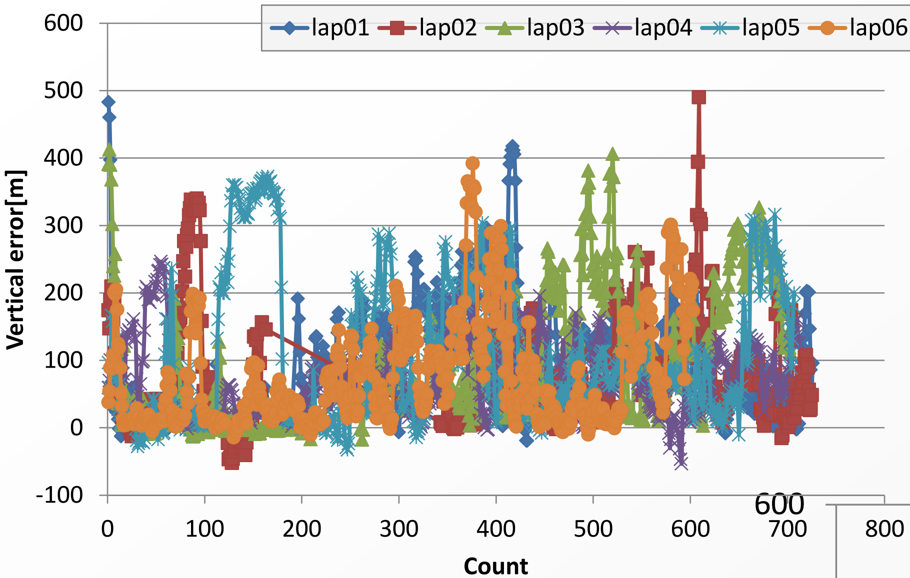
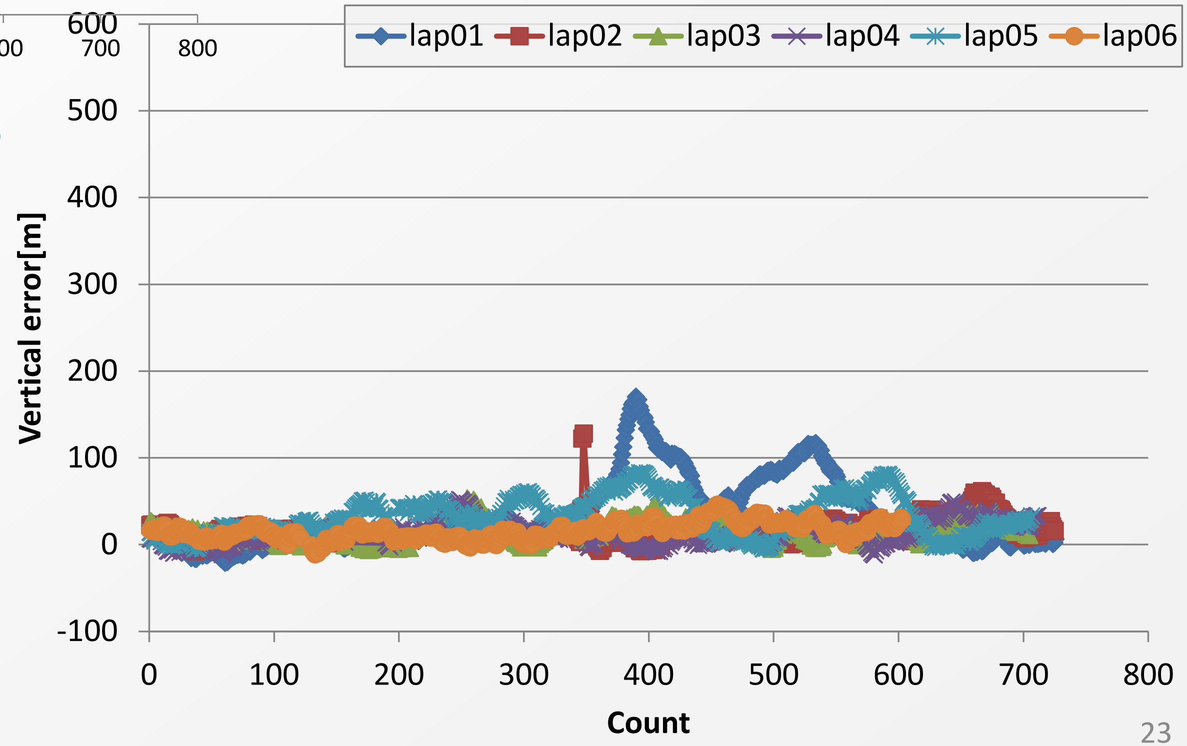


Conventional EKF

Adaptive EKF



Statistics for position error

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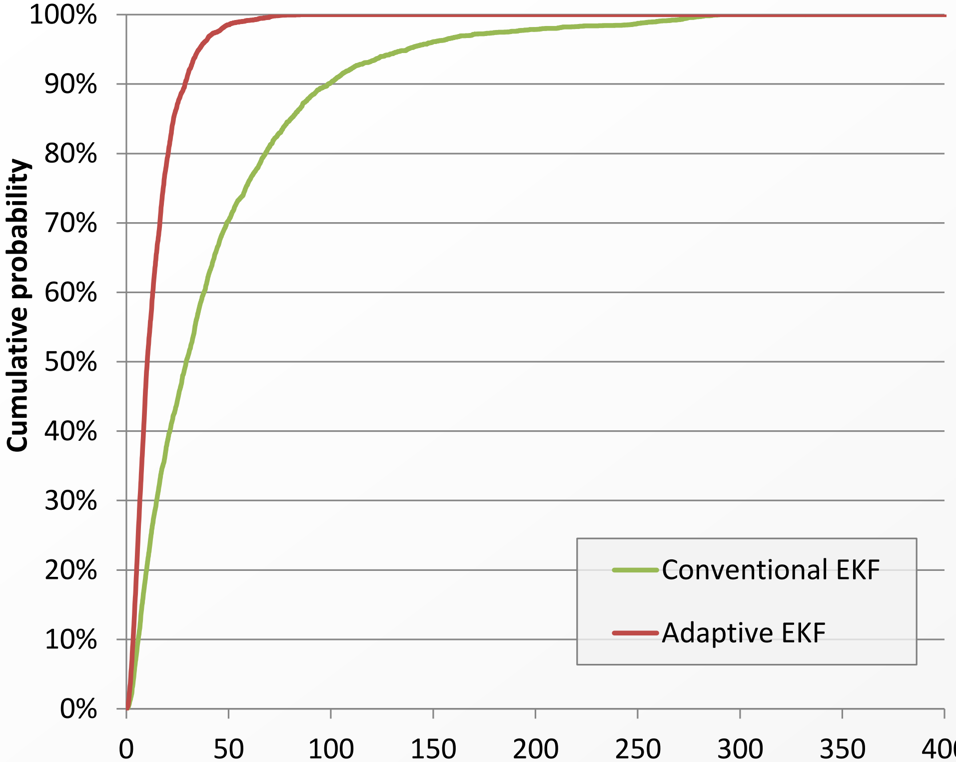
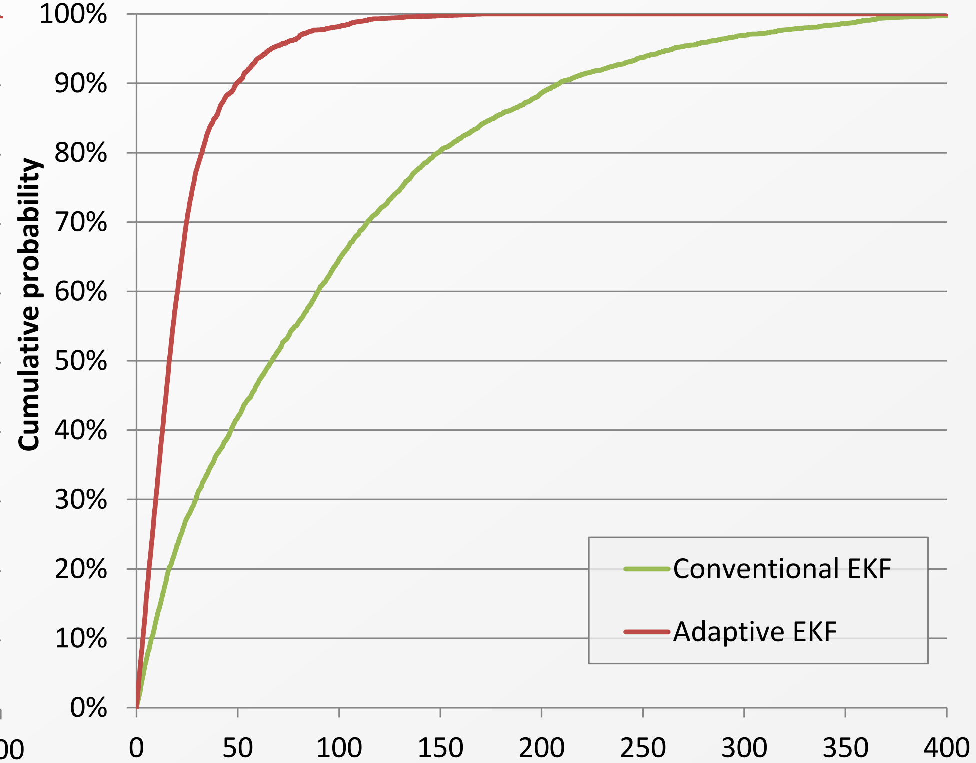
Horizontal CDF



Vertical CDF



		Mean error[m]	Error at 68.27%[m]	Error at 95.45%[m]	Error at 100%[m]
Horizontal	Adaptive EKF	2.50	15.9	36.6	85.0
	Conventional EKF	13.35	46.7	141.6	290.0
Vertical	Adaptive EKF	21.44	23.9	70.6	170.0
	Conventional EKF	88.89	109.6	272.9	490.2

Velocity error

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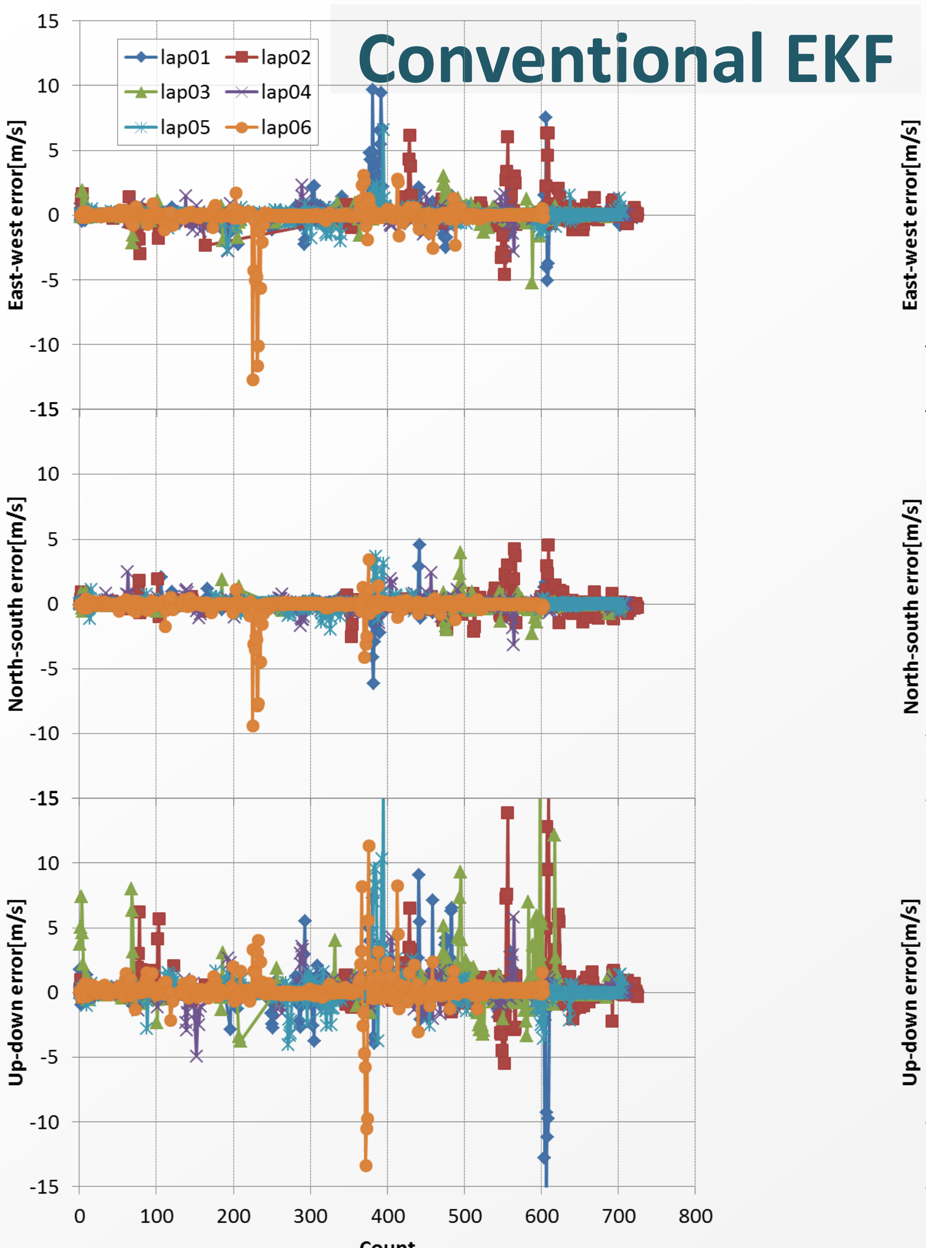

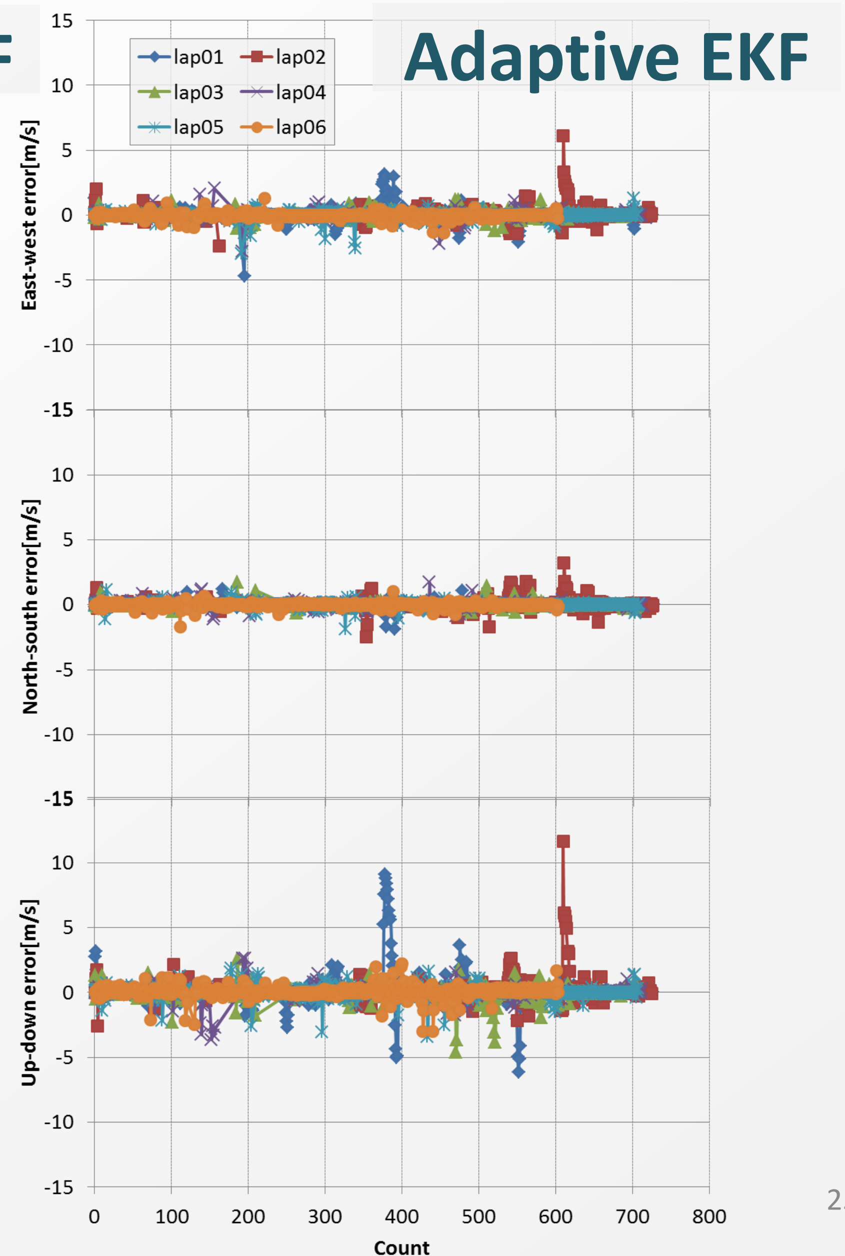

Statistics for velocity error

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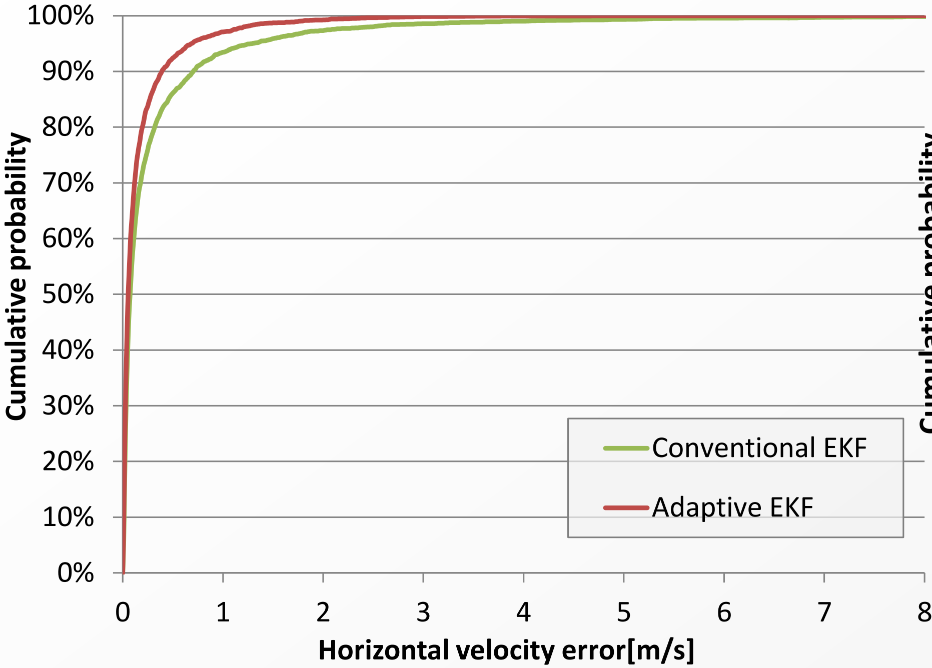
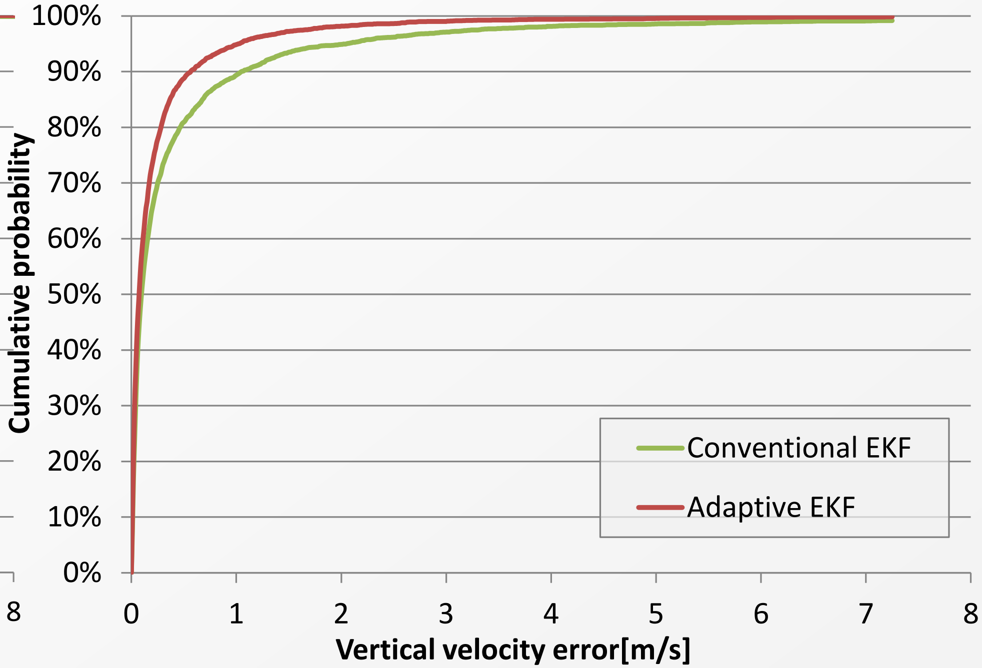
Horizontal CDF



Vertical CDF



		Mean error[m/s]	Error at 68.27%[m/s]	Error at 95.45%[m/s]	Error at 100%[m/s]
Horizontal	Adaptive EKF	0.010	0.12	0.73	6.92
	Conventional EKF	0.027	0.16	1.39	15.80
Vertical	Adaptive EKF	0.033	0.16	1.07	11.63
	Conventional EKF	0.146	0.23	2.19	-16.91

Summary for positioning

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- The adaptive EKF achieved the impressive GNSS performance using the mass-product receiver in the dense urban environment.
  - The positioning accuracy and precision are drastically improved comparing with the conventional EKF.

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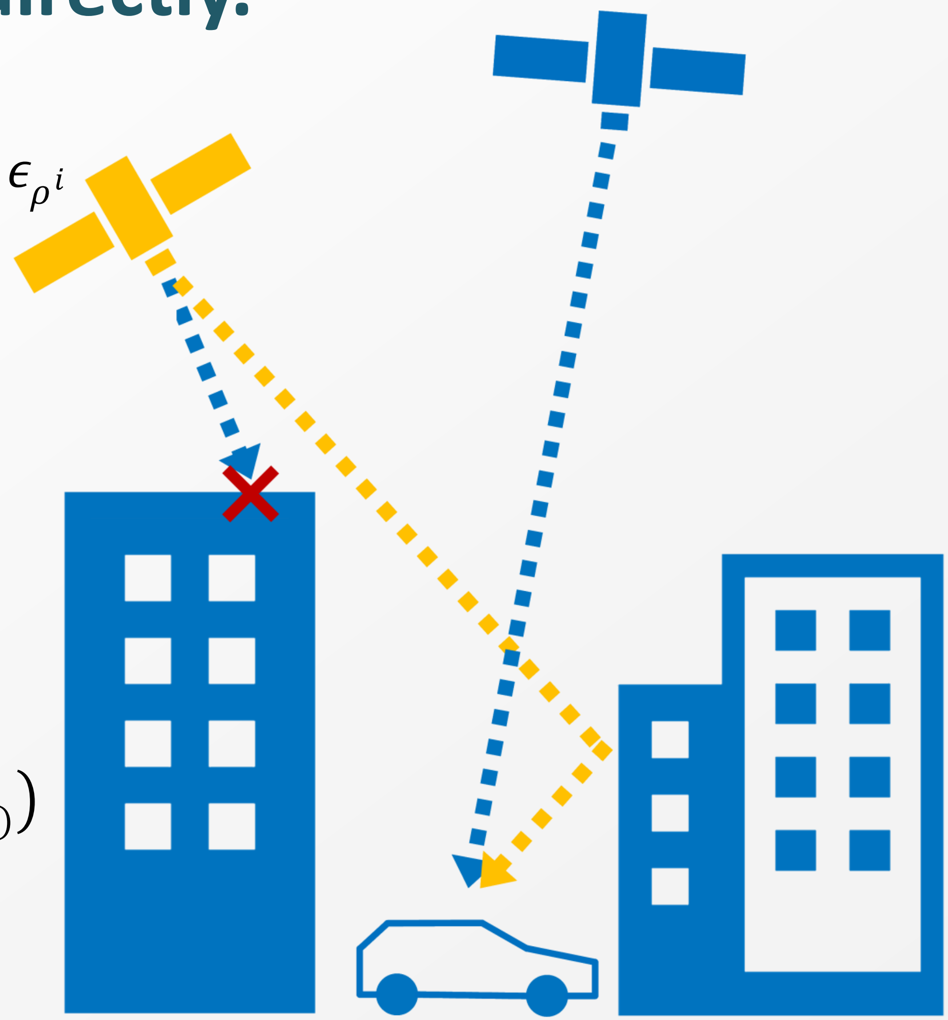
NLOS bias on measurement

- **Residuals of single difference gives NLOS bias directly.**

$$\rho^{QZSS} = \gamma^{QZSS} + \delta t + \epsilon_{\rho^{QZSS}}$$

$$\rho^{i} = \gamma^{i} + \delta t + \boxed{\delta^{i}_{NLOS}} + \epsilon_{\rho^{i}}$$



$$\Delta\rho^{QZSS,i}_{(residual)} = (\rho^{i} - \rho^{QZSS}) - \left(\gamma^{i}_{(true)} - \gamma^{QZSS}_{(true)}\right) = \boxed{\delta^{i}_{NLOS}} + \epsilon_{\Delta\rho^{QZSS,i}}$$

GPS PR error (lap04)

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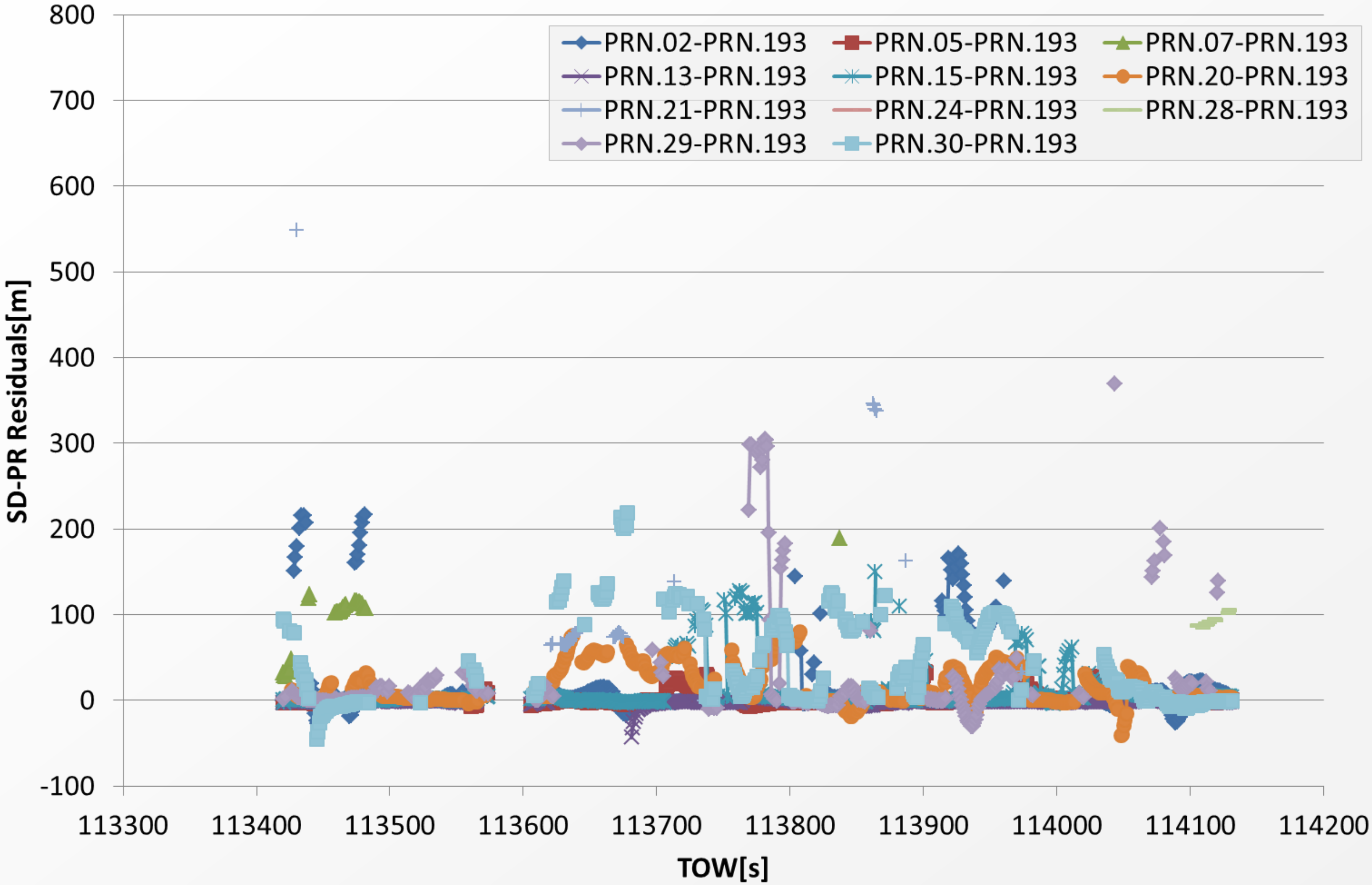

GLO PR error (lap04)

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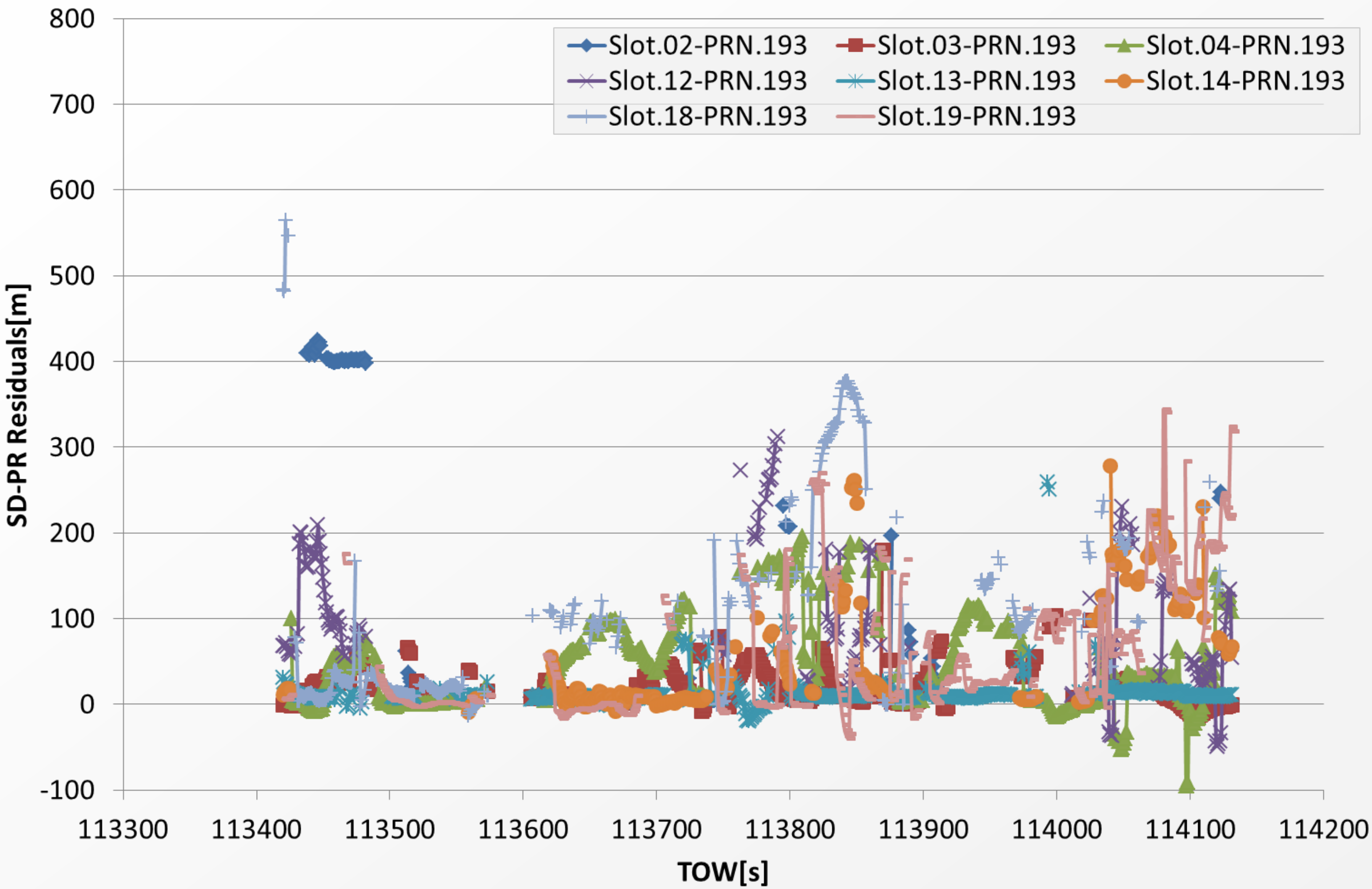

GPS RR error (lap04)

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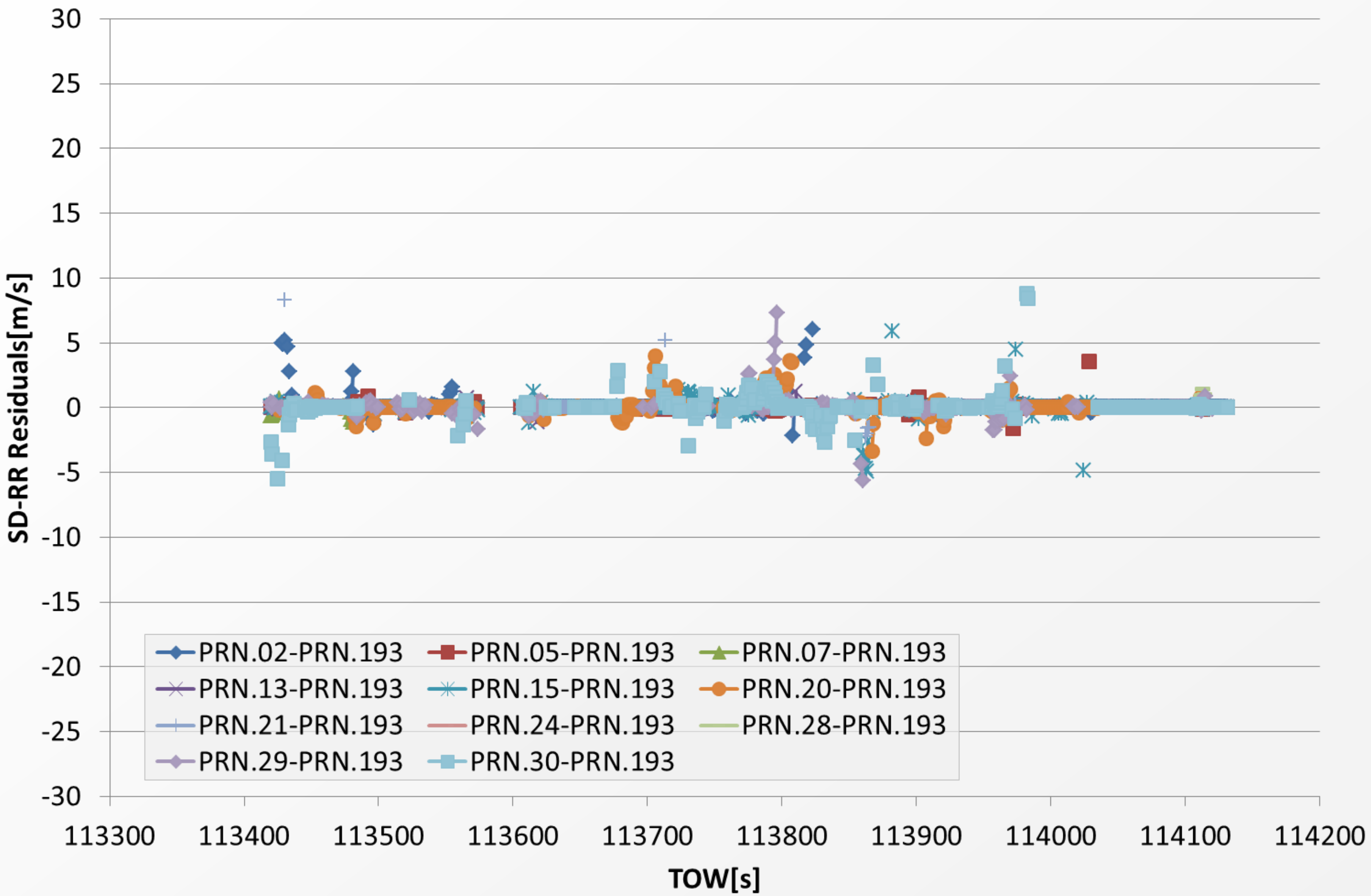
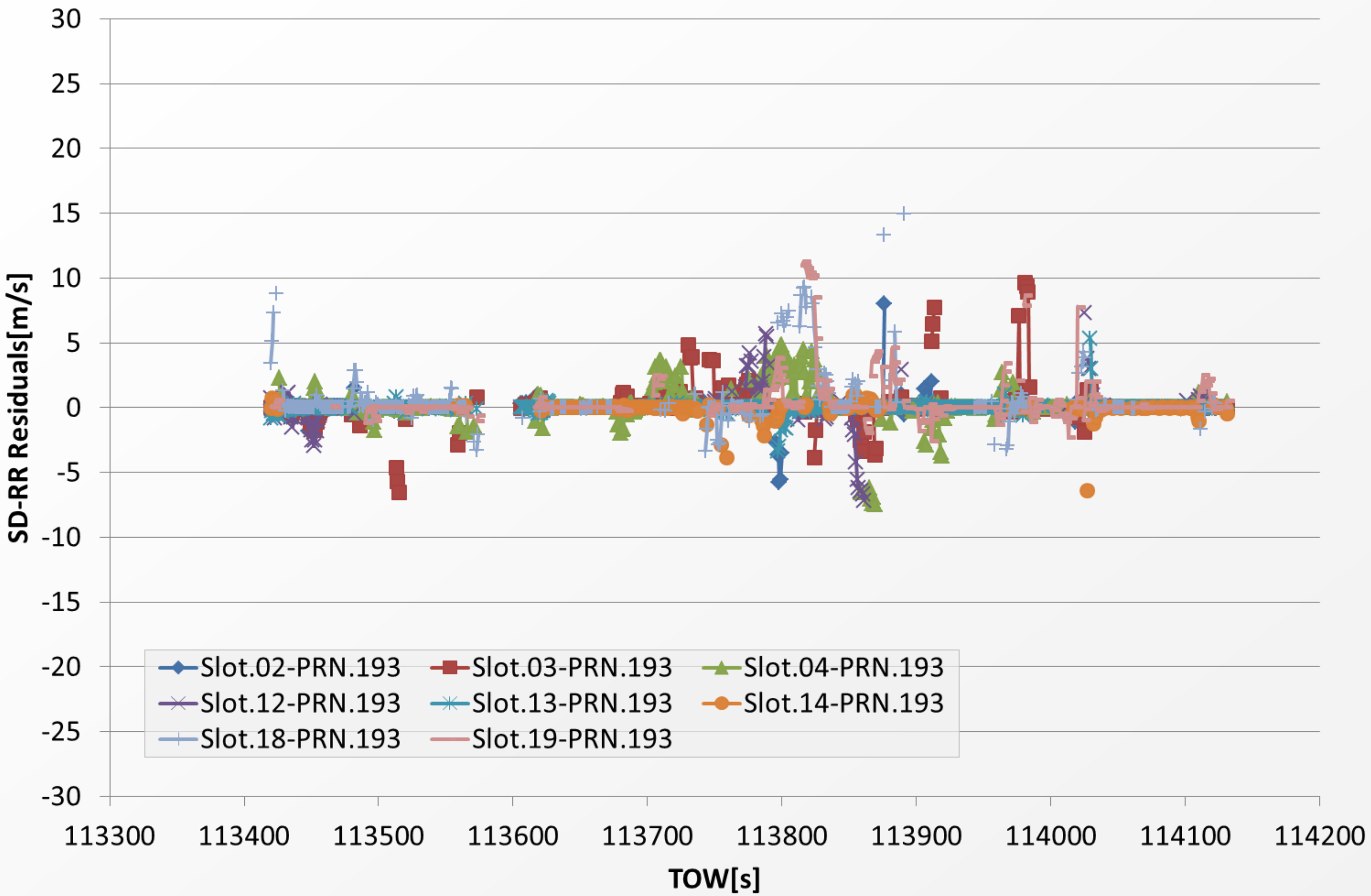


GLO RR error (lap04)



GPS PR error vs Adaptive σ (lap04)

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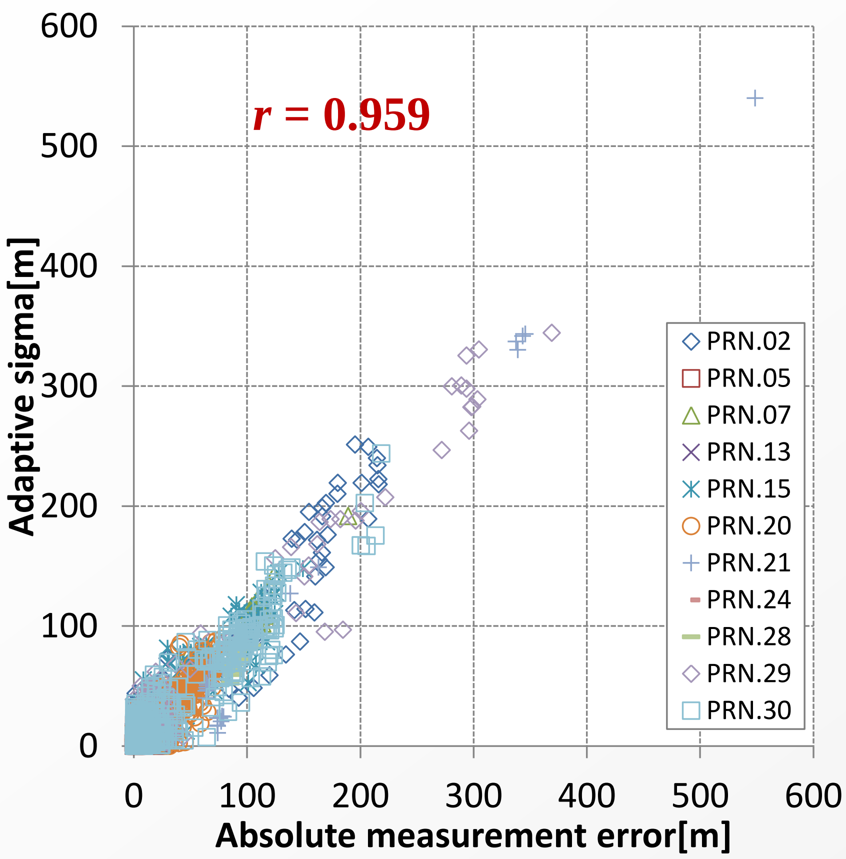

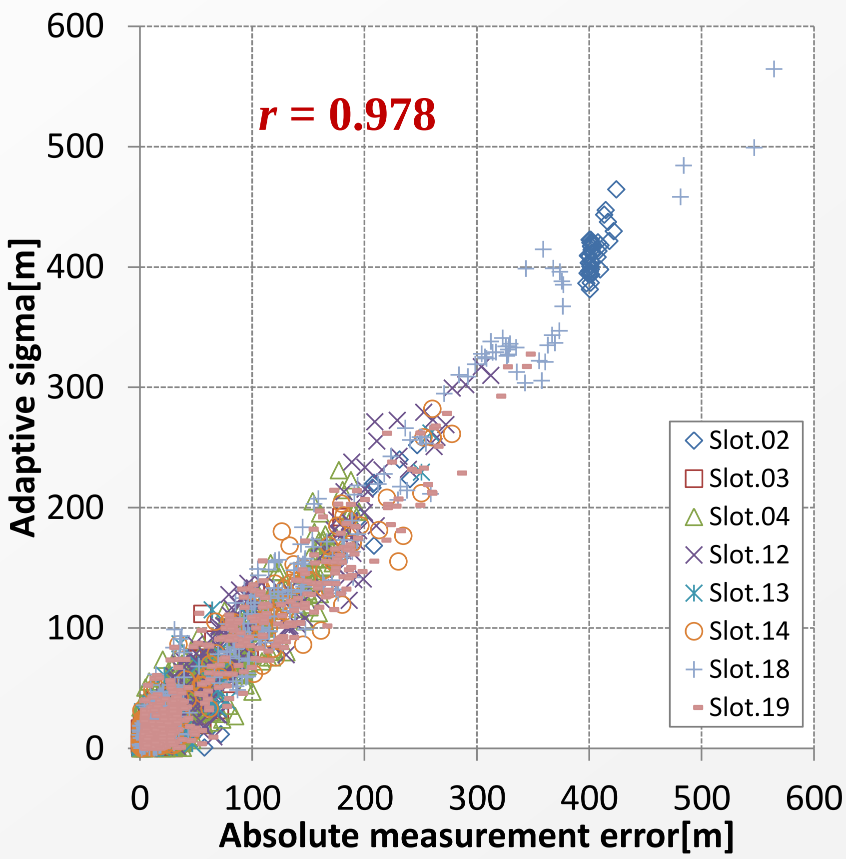

GLO PR error vs Adaptive σ (lap04)

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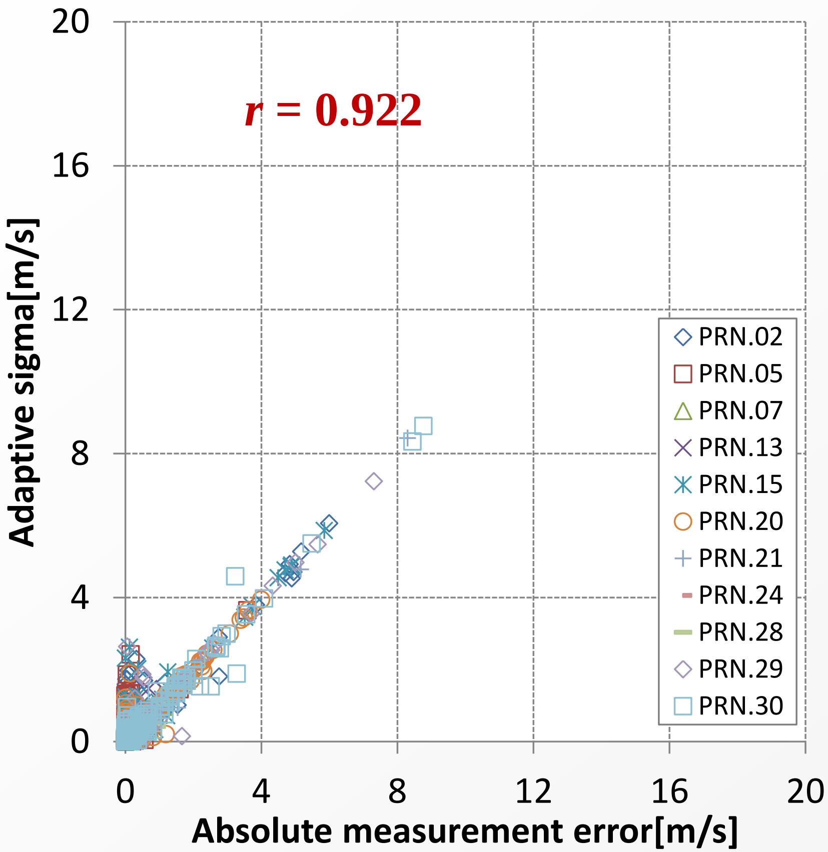
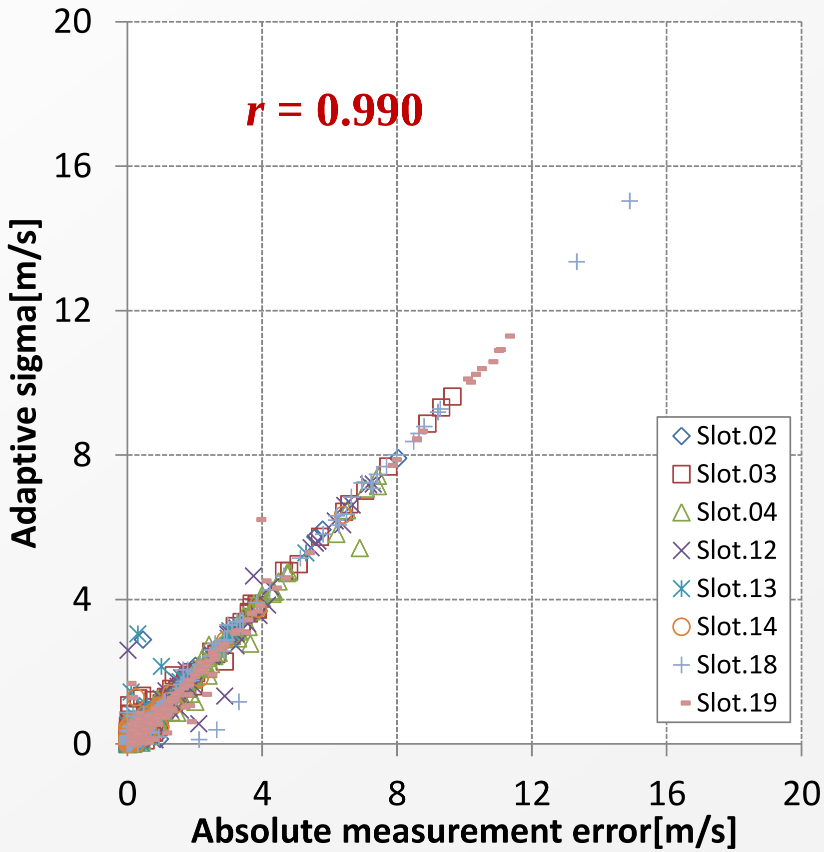
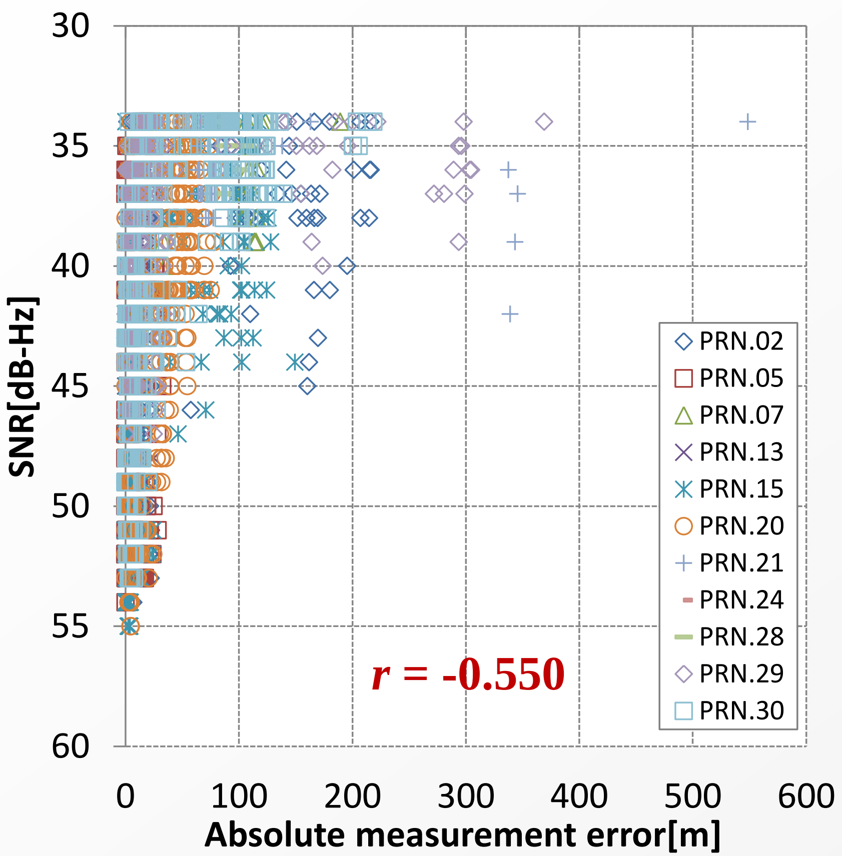
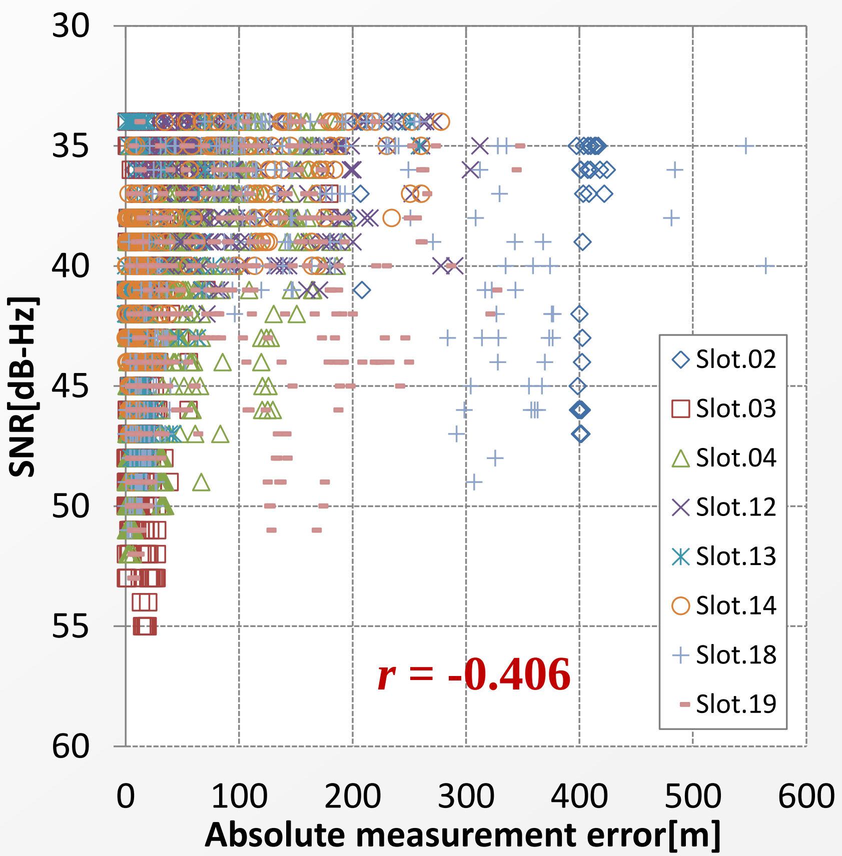


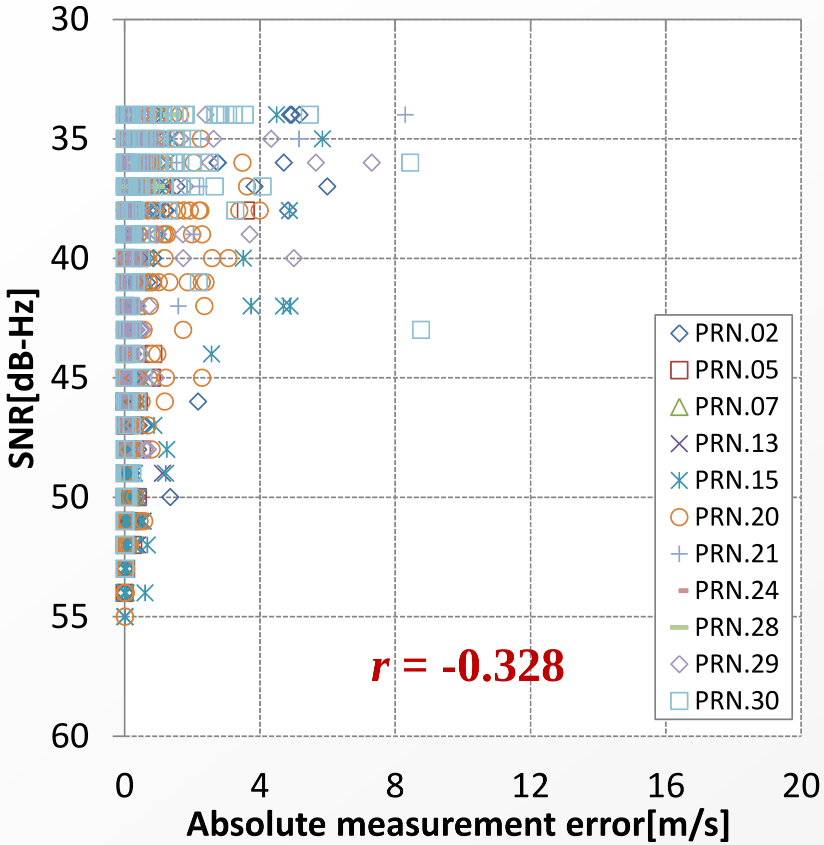


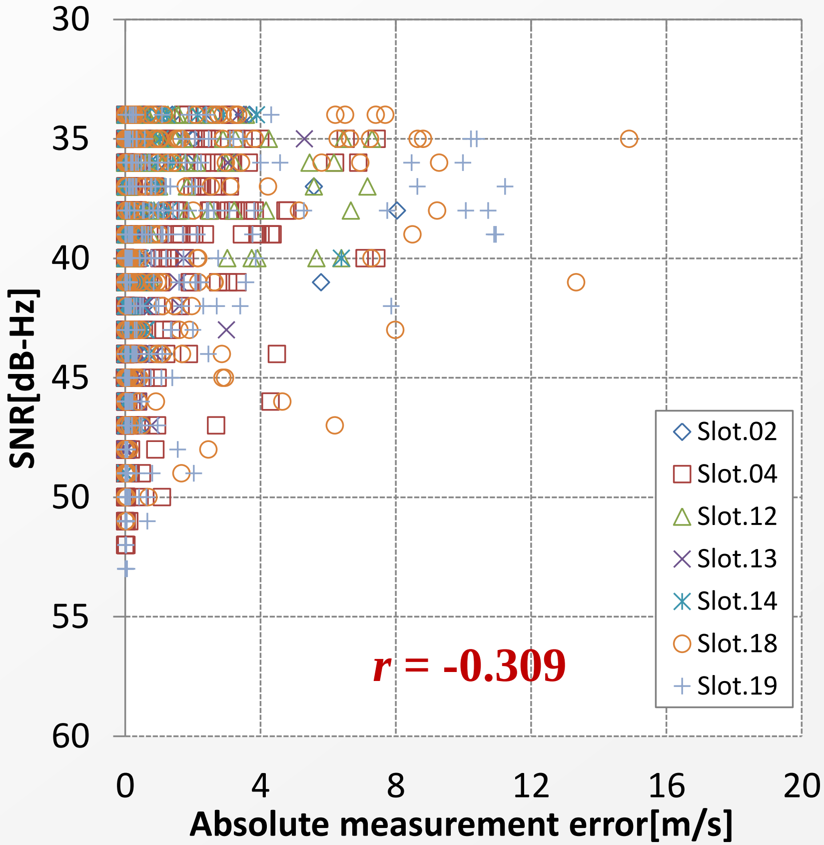
PR error vs SNR (lap04)





RR error vs SNR (lap04)





Summary for meas. error

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- Large NLOS bias can be found in both pseudo-range and Doppler measurements.

- Adaptive σ matched the NLOS bias well.
  - While it was the challenge for conventional SNR-based σ estimation.
  - This is the exact reason why the single point positioning performance by the Adaptive EKF improved.

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Integrity information

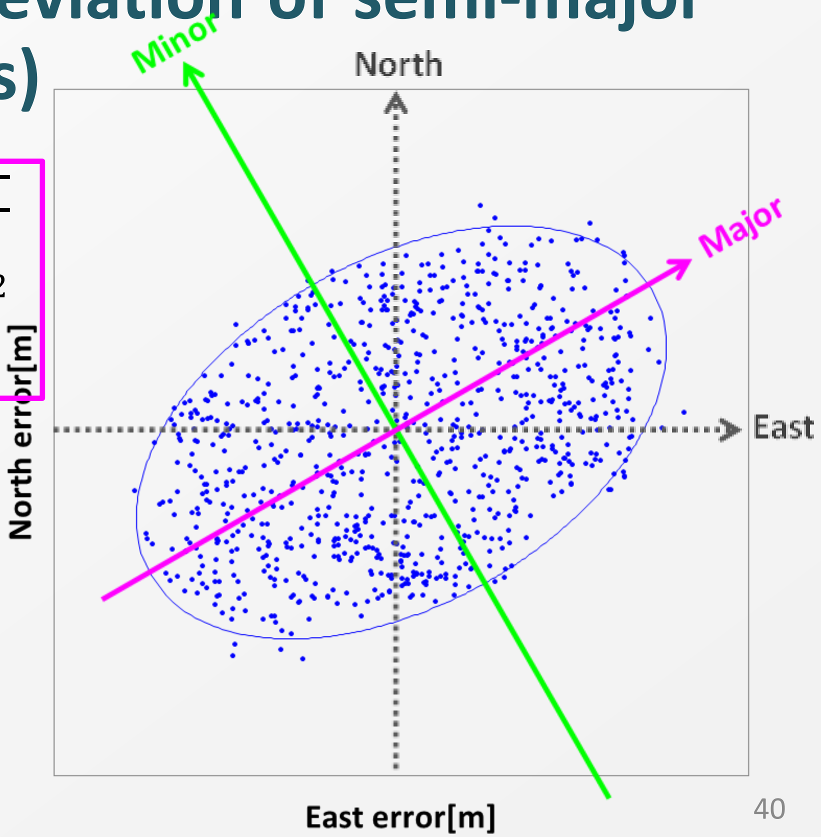
- RTCA defines HPL (Horizontal Protection Level) and VPL (Vertical Protection Level) regarding to standard deviations.
  - Error ellipsoid: Standard deviation of semi-major axis of error ellipse (meters)

$$\sigma_{Hmajor} = \sqrt{\frac{{\sigma_e}^2 + {\sigma_n}^2}{2} + \sqrt{\left(\frac{{\sigma_e}^2 - {\sigma_n}^2}{2}\right)^2 + {\sigma_{en}}^2}}$$

$$HPL = k \cdot \sigma_{Hmajor}$$

$$VPL = k \cdot \sigma_u$$

  - RTCA suggests k=6.



PLs from covariance matrix

- Rotate the covariance matrix of the state vector from ECEF to ENU coordinates frame.

$$\boldsymbol{P}_{\boldsymbol{g}_{u,ENU}} = \boldsymbol{T}^T \boldsymbol{P}_{\boldsymbol{g}_u} \boldsymbol{T} = \begin{pmatrix} {\sigma_e}^2 & \sigma_{en} & \sigma_{eu} \\ \sigma_{ne} & {\sigma_n}^2 & \sigma_{nu} \\ \sigma_{ue} & \sigma_{un} & {\sigma_u}^2 \end{pmatrix}$$

  – where $\boldsymbol{T}$ is a rotation matrix from ECEF to ENU coordinates.
  – This rotation serves HPL and VPL computation.

Applying IAE to GNSS

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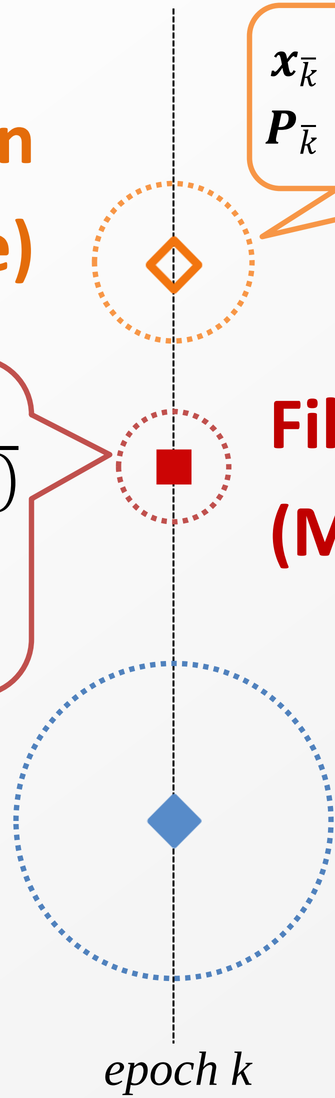
- **Summary for extended-Kalman filter (EKF)**

Prediction (Time update)

$$\boldsymbol{x}_{\bar{k}} = \boldsymbol{F}_k \boldsymbol{x}_{k-1} + \boldsymbol{D}_k \boldsymbol{u}_k$$
$$\boldsymbol{P}_{\bar{k}} = \boldsymbol{F}_k \boldsymbol{P}_{k-1} \boldsymbol{F}_{k-1}^T + \boldsymbol{Q}_k$$

Filter (Measurement Update)

$$\boldsymbol{K}_k = \frac{\boldsymbol{P}_{\bar{k}} \boldsymbol{H}(\boldsymbol{x}_{\bar{k}})^T}{\left(\boldsymbol{H}(\boldsymbol{x}_{\bar{k}}) \boldsymbol{P}_{\bar{k}} \boldsymbol{H}(\boldsymbol{x}_{\bar{k}})^T + \widehat{\boldsymbol{R}}_k\right)}$$
$$\boldsymbol{x}_k = \boldsymbol{x}_{\bar{k}} + \boldsymbol{K}_k\left(\boldsymbol{z}_k - \boldsymbol{h}(\boldsymbol{x}_{\bar{k}})\right)$$
$$\boldsymbol{P}_k = \left(\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}(\boldsymbol{x}_{\bar{k}})\right)\boldsymbol{P}_{\bar{k}}$$



Measurement

$\boldsymbol{z}_k$

$\widehat{\boldsymbol{R}}_k$

Adaptive covariance matrix of measurement noise

Stanford diagram

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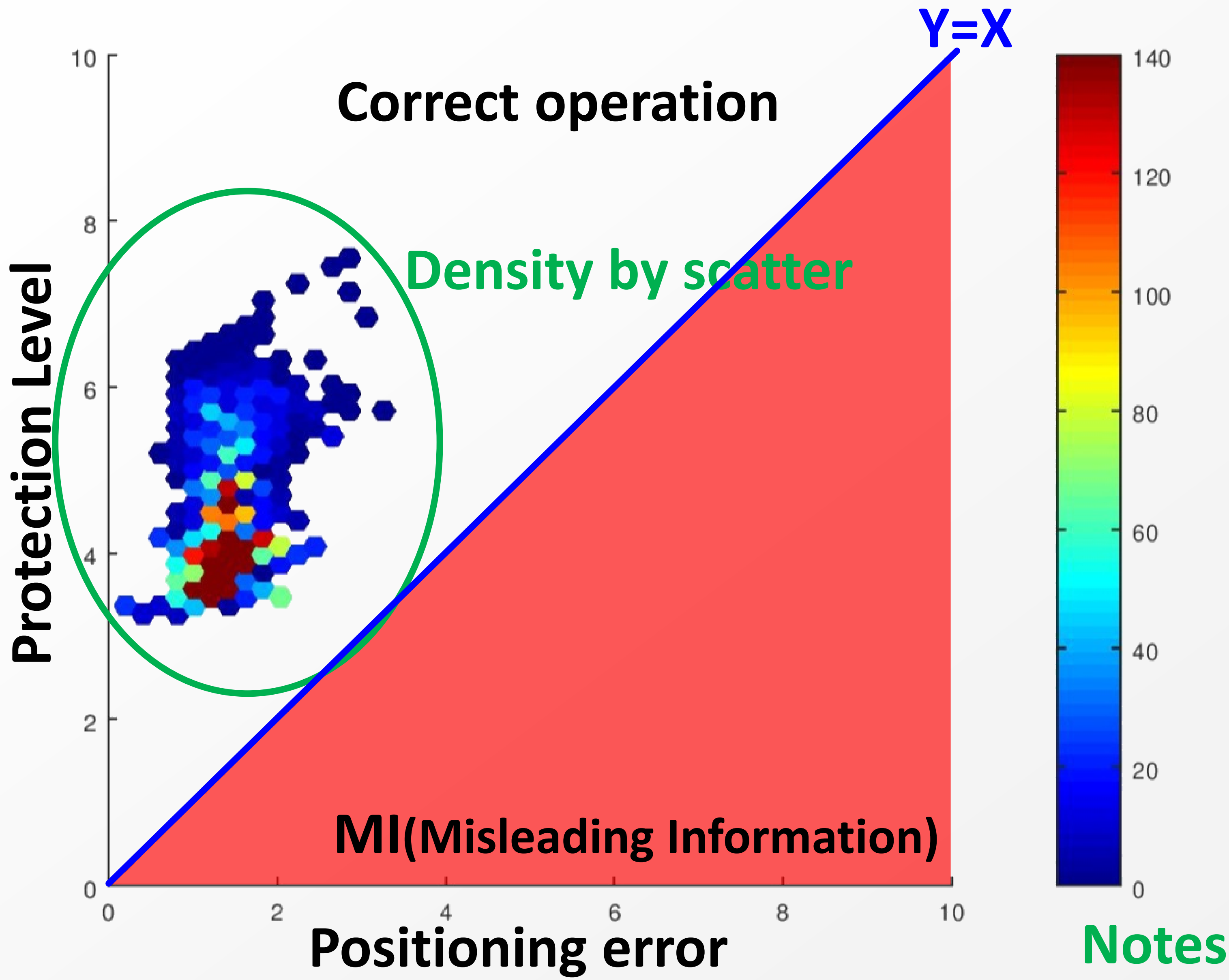

HPLpos by Conventional EKF

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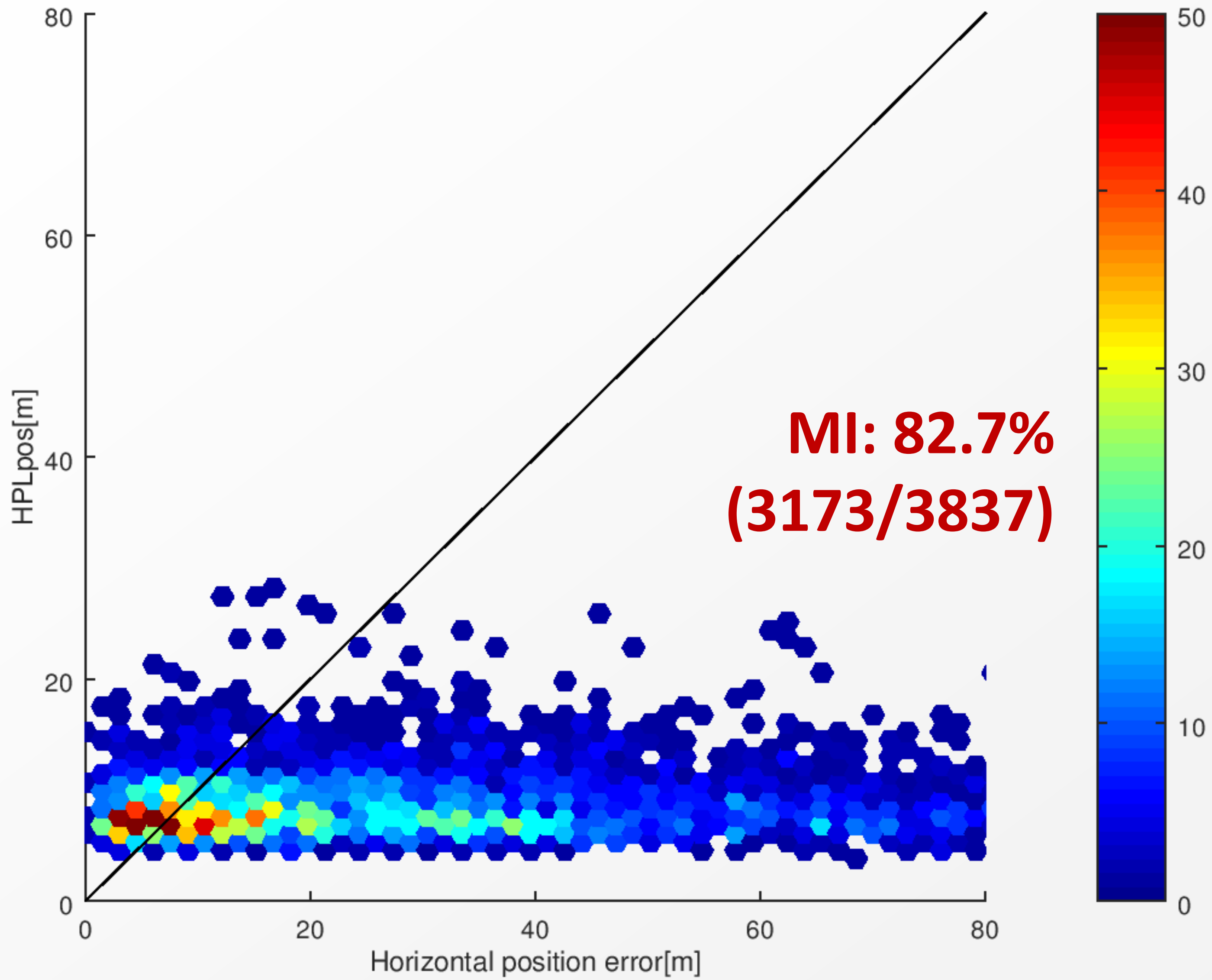

HPLpos by Adaptive EKF

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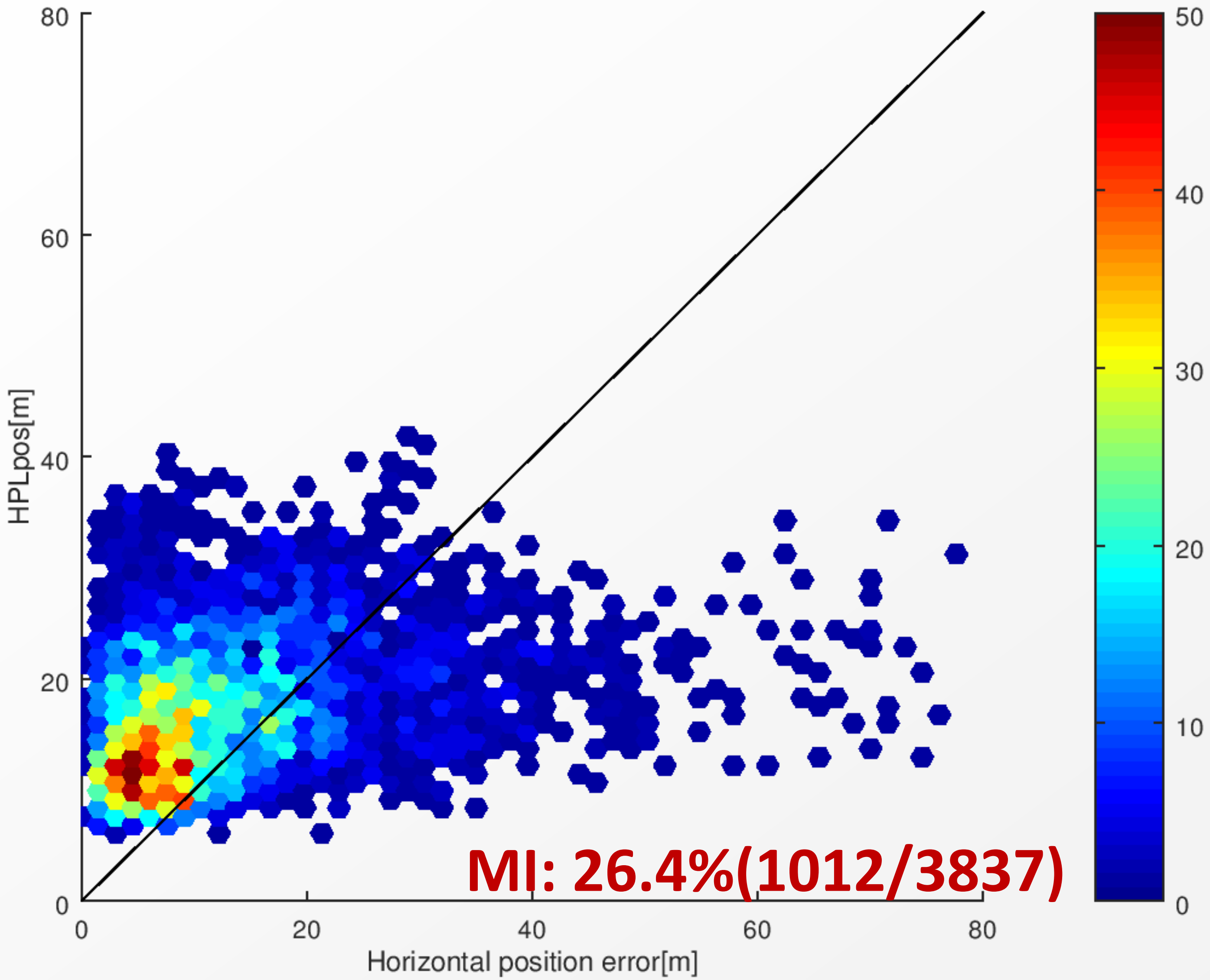

VPLpos by Conventional EKF

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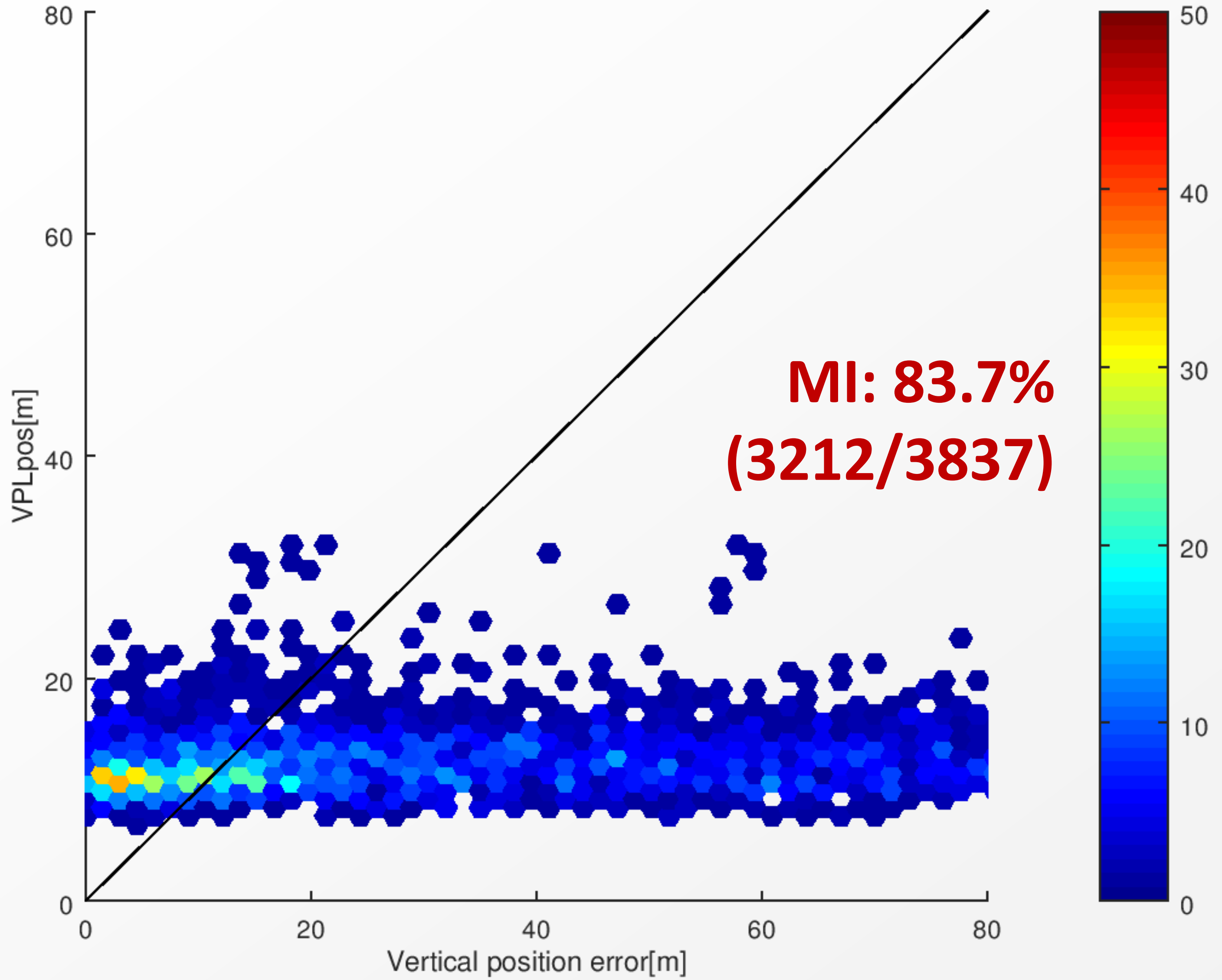

VPLpos by Adaptive EKF

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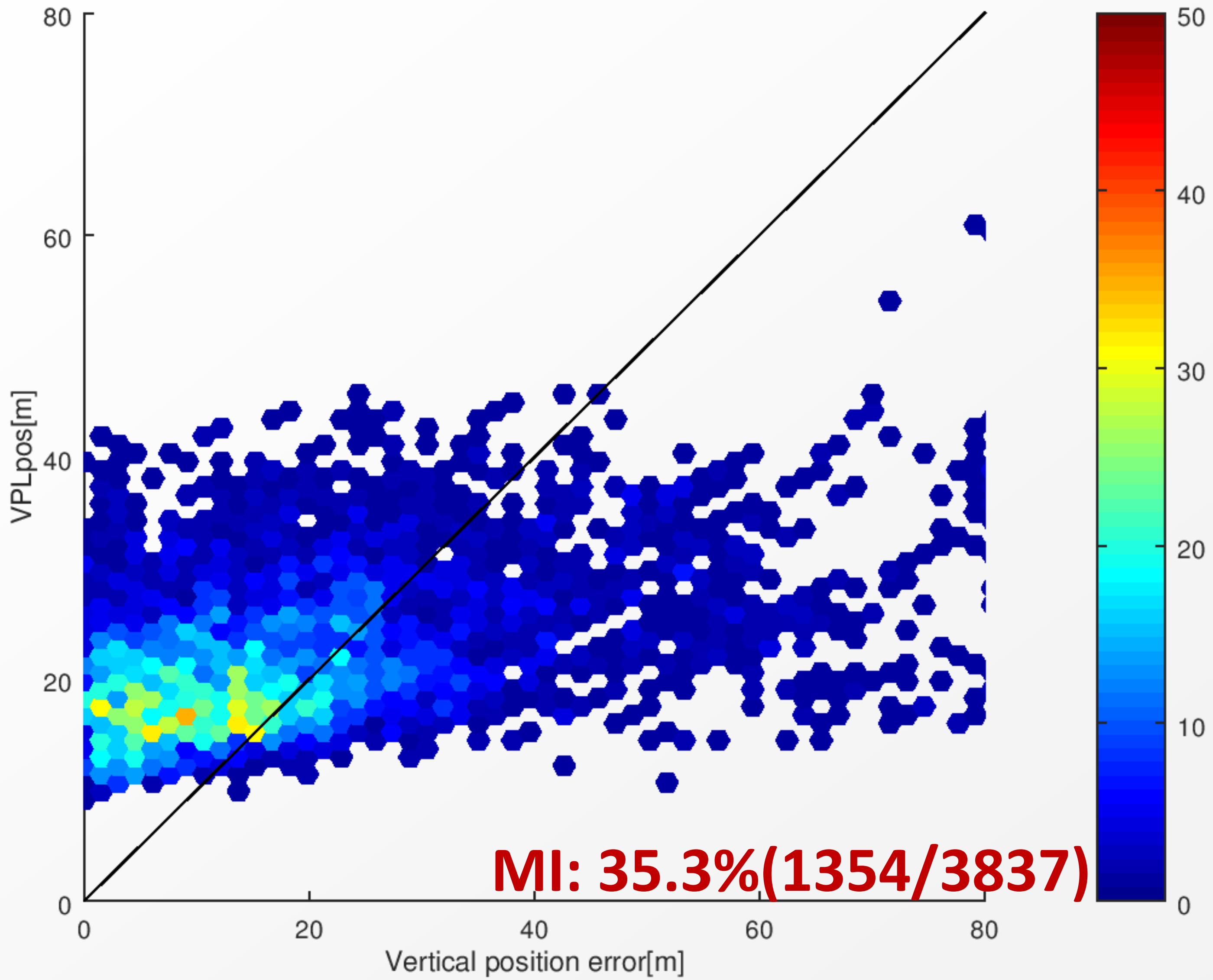

Summary for Integrity

- Protection Levels by the conventional EKF degraded.
  - No longer the integrity information.

- Adaptive EKF restrained the degradation.
  - MI stood at the marginal.

Agenda

- Introduction to Adaptive Kalman Filter
  - Kalman filter
  - IAE(Innovation-based Adaptive Estimation)
  - Applying IAE to GNSS
- Adaptive EKF vs. Urban Canyon
  - Positioning accuracy and precision
  - Measurement error and predicted sigma
  - Integrity Information
- Conclusion and future works

Conclusion

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- **The adaptive EKF achieved the impressive GNSS performance using the mass-product receiver in the dense urban environment:**
  - **The positioning accuracy and precision are drastically improved comparing with the conventional EKF.**
  - **Adapted covariance matrix matched the actual measurement errors well,**
    - **It was the challenge for the conventional SNR-based estimation.**
  - **Integrity information degraded by the conventional EKF, while adaptive EKF restrained the degradation.**

Future works

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- The ideal MI (Miss-leading Information) is 0%.
  - Further investigation and improvement are necessary to establish more robust integrity information.
  - Alternate detection methods of outliers must be considered:
    - Residual-based test
    - Solution separation

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    - collecting test drive data

Thank you very much for your kind attention!

Measurement model

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- **GNSS pseudo-range measurement can be modeled by simply:**

$$\rho^i = \gamma^i + \delta t + \epsilon_{\rho^i}$$

$$\gamma^i = \left\| \boldsymbol{g}^i - \boldsymbol{g}_u \right\|$$

$$= \sqrt{(x^i - x_u)^2 + (y^i - y_u)^2 + (z^i - z_u)^2}$$

  - **Then, linearize by Taylor series:**

$$\rho^i \sim \left(\sqrt{(x^i - x_0)^2 + (y^i - y_0)^2 + (z^i - z_0)^2} + \delta t_0 \right) + \frac{(x^i - x_0)\Delta x + (y^i - y_0)\Delta y + (z^i - z_0)\Delta z}{\sqrt{(x^i - x_0)^2 + (y^i - y_0)^2 + (z^i - z_0)^2}} + \Delta\delta t + \epsilon_{\rho^i}$$

Horizontal pos. error (lap04)

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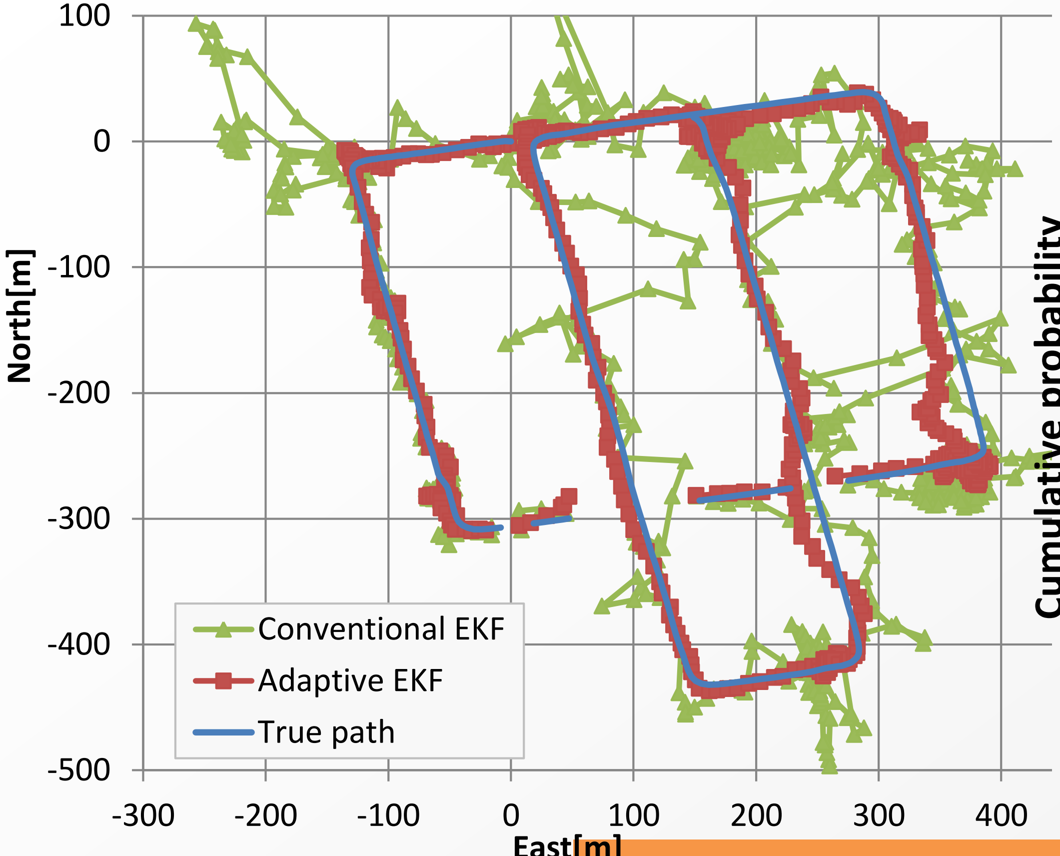

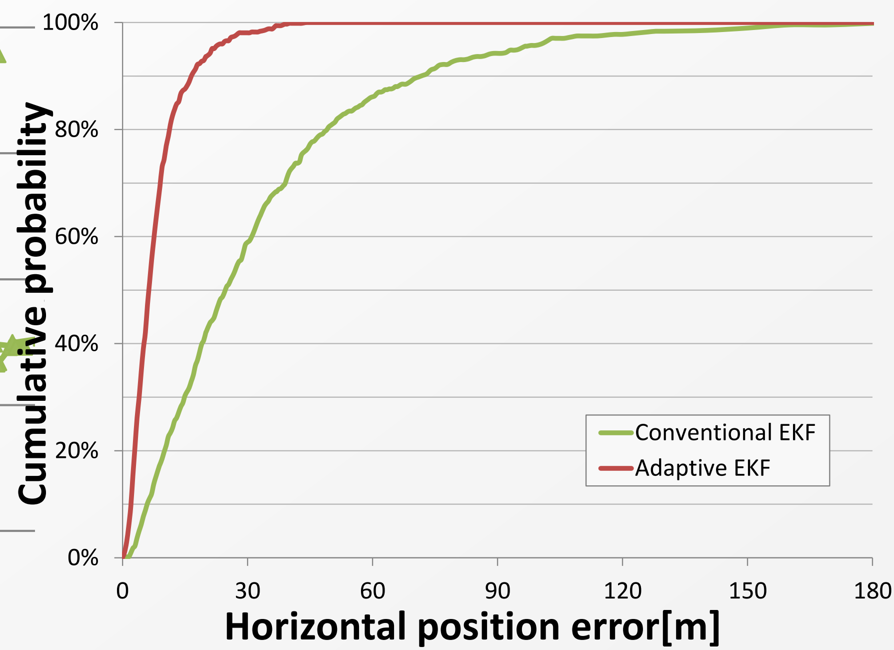

	Mean error[m]	Erro at 68.27%[m]	Erro at 95.45%[m]
Adaptive EKF	1.58	8.9	22.5
Conventional EKF	7.38	36.8	96.6

Vertical pos. error (lap04)

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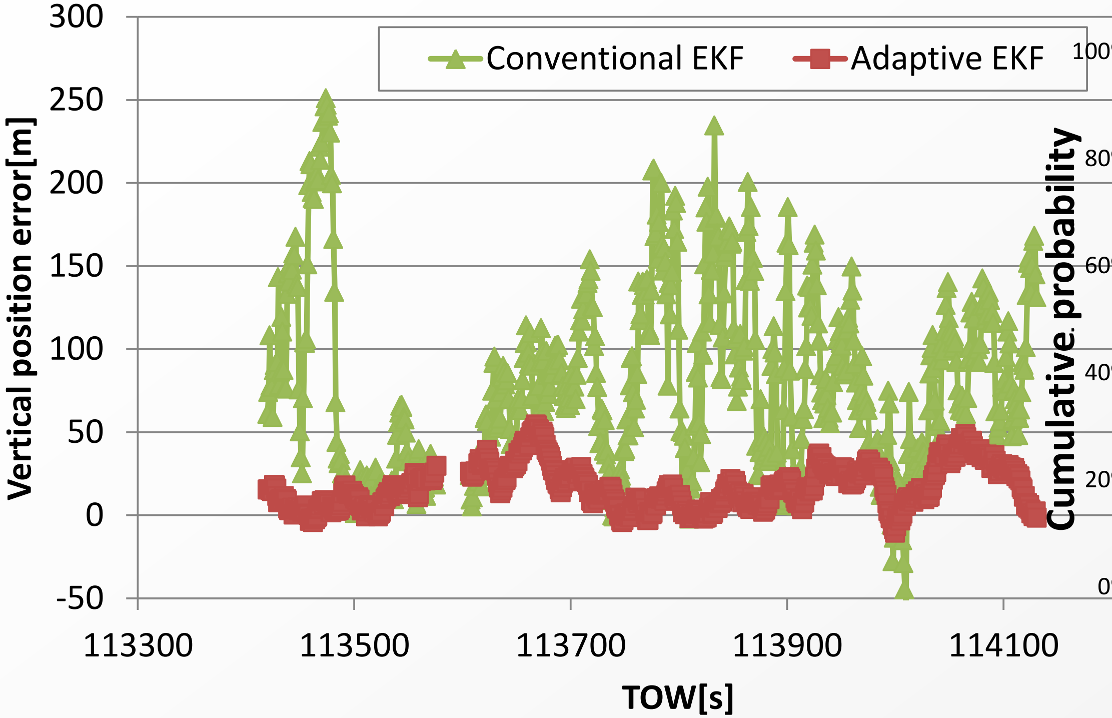

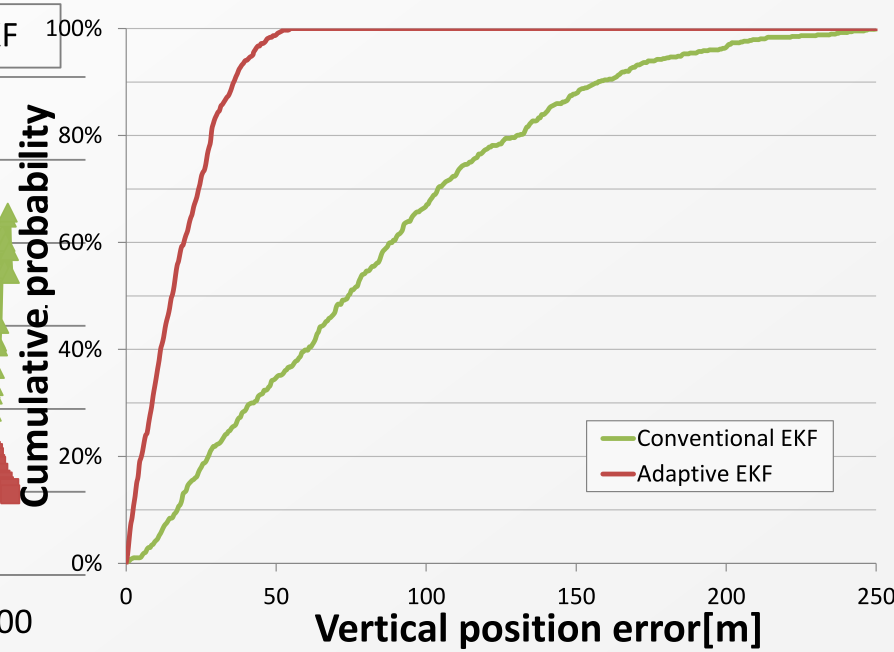

	Mean error[m]	Erro at 68.27%[m]	Erro at 95.45%[m]
Adaptive EKF	17.16	23.6	42.5
Conventional EKF	80.43	102.0	180.4

PR NLOS error

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	GPS/QZSS			GLONASS		
	Mean [m/s]	StDev [m/s]	Max [m/s]	Mean [m/s]	StDev [m/s]	Max [m/s]
Lap01	32.9	66.9	593.4	20.2	41.6	297.5
Lap02	43.1	94.0	530.8	24.6	48.5	477.4
Lap03	33.5	77.8	491.8	50.5	87.3	516.9
Lap04	14.0	38.6	548.6	53.4	82.5	564.5
Lap05	34.8	83.6	542.8	33.9	77.2	731.3
Lap06	33.9	84.4	576.1	21.6	55.8	531.7

Doppler NLOS error

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	GPS/QZSS			GLONASS		
	Mean [m/s]	StDev [m/s]	Max [m/s]	Mean [m/s]	StDev [m/s]	Max [m/s]
Lap01	0.06	1.74	-23.11	0.05	1.15	-14.97
Lap02	0.27	2.03	16.90	0.14	1.24	9.92
Lap03	0.15	1.28	23.74	0.44	2.57	24.68
Lap04	0.04	0.59	8.77	0.20	1.44	14.90
Lap05	0.04	1.19	-18.27	0.12	1.58	23.06
Lap06	0.20	1.77	20.15	0.09	1.12	16.80

Adaptive σ vs. meas error

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	GPS/QZSS		GLONASS	
	Pseudo-range	Doppler shift	Pseudo-range	Doppler shift
Lap01	0.932	0.954	0.949	0.976
Lap02	0.990	0.982	0.953	0.954
Lap03	0.983	0.982	0.980	0.996
Lap04	0.959	0.922	0.978	0.990
Lap05	0.979	0.979	0.954	0.987
Lap06	0.989	0.990	0.979	0.989

SNR vs. meas error

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	GPS/QZSS		GLONASS	
	Pseudo-range	Doppler shift	Pseudo-range	Doppler shift
Lap01	-0.517	-0.265	-0.592	-0.276
Lap02	-0.528	-0.357	-0.503	-0.421
Lap03	-0.455	-0.288	-0.521	-0.292
Lap04	-0.550	-0.328	-0.406	-0.309
Lap05	-0.405	-0.232	-0.468	-0.254
Lap06	-0.494	-0.206	-0.549	-0.273

Stanford diagram

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