KAIST

Vertical Position Error Bounding for Integrated Sensors to Support Unmanned Aerial Vehicles (UAVs)

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Stanford University

UAV Applications
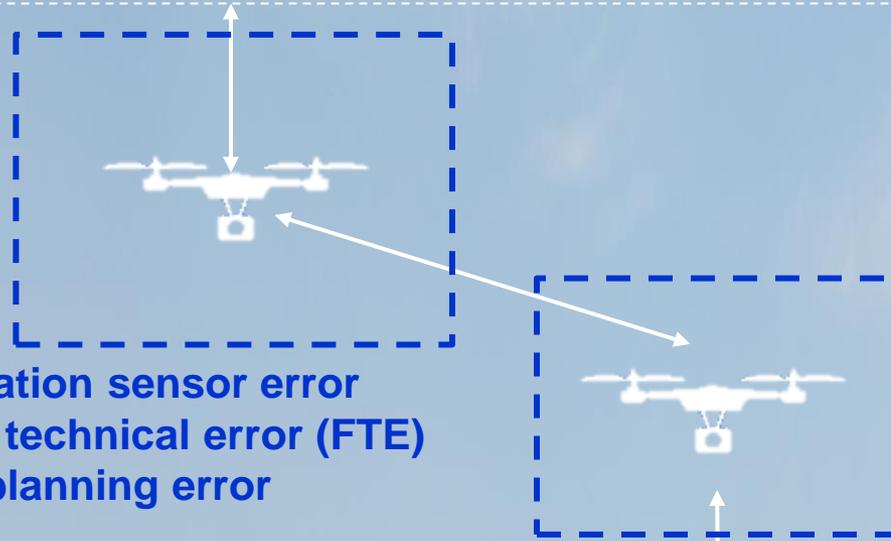
Amazon's Delivery Drone

Source: CBS News, Dec. 2013

Project Wing by Google

Source: New York Times, Aug. 2014

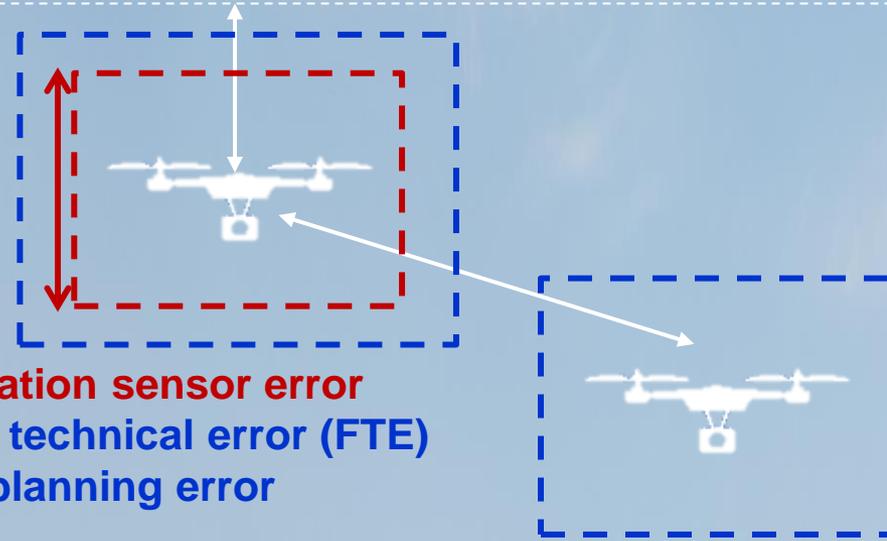# UAV Operational environment

- **Navigation sensor error**
- **Flight technical error (FTE)**
- **Path planning error**
- **etc**

Goal: Vertical navigation error bound for UAV

- **Navigation sensor error**
- **Flight technical error (FTE)**
- **Path planning error**
- **etc**

Provide vertical navigation error bound for UAV based on their navigation sensors and algorithm

Outline

Local-Area Differential (LAD) GNSS for UAV Network Operations

- **KAIST LAD-GNSS Test-bed Hardware Configuration**
- **UAV flight test to simulate vertical navigation error bounding with LAD-GNSS**

UAV vertical position error bounding for integrated sensors

- **UAV navigation sensors and algorithms**
- **Error models for integrated sensors**
- **Simulation results using derived error models for each sensor scenarios**

Outline

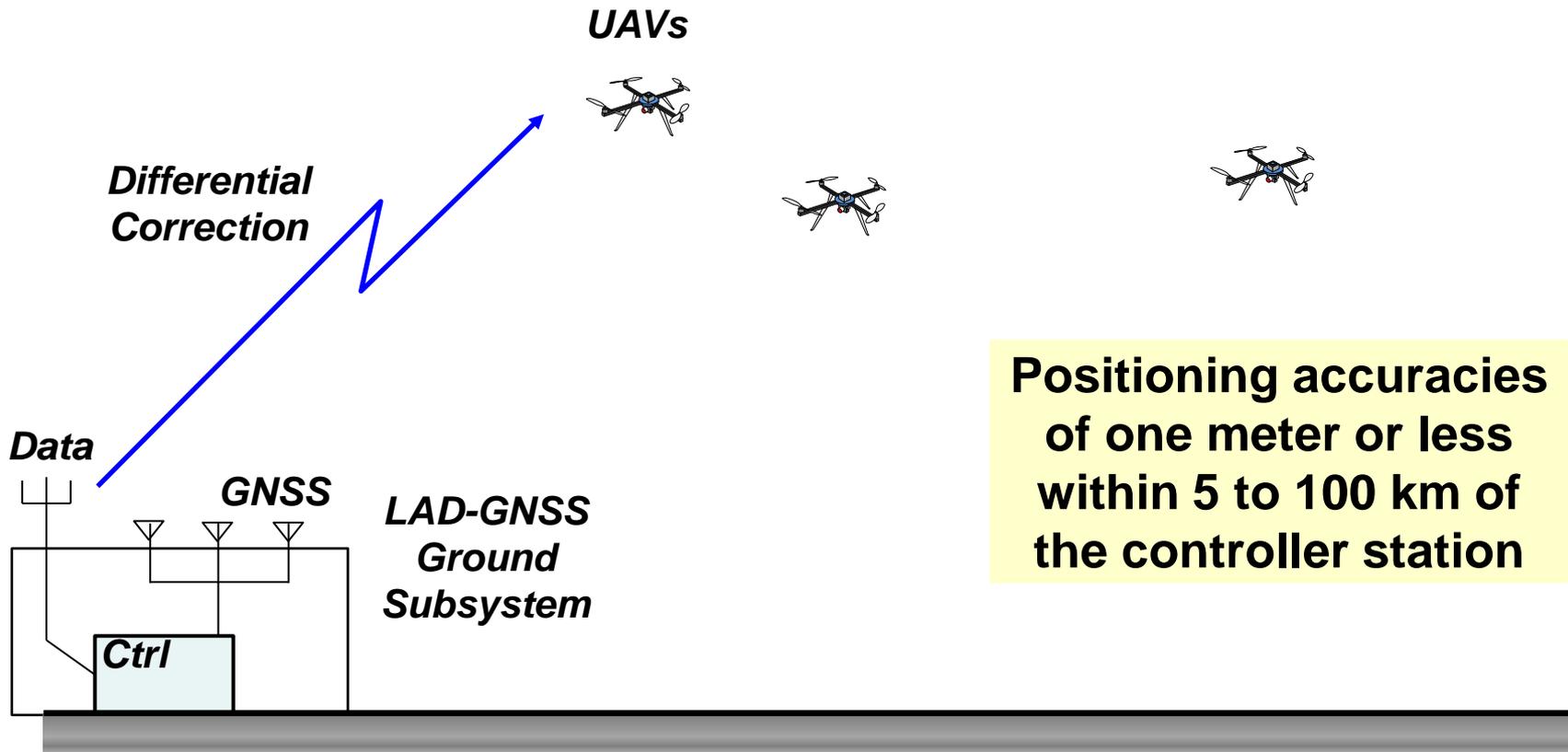**Local-Area Differential (LAD) GNSS for UAV Network Operations**

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Local-Area Differential (LAD) GNSS for UAV Network Operations

- Prior work proposed LADGNSS architectures to provide increased accuracy, safety, and reliable navigation to UAVs [S. Pullen, et al, ION ITM 2013].

UAVs

Differential Correction

Data

GNSS

LAD-GNSS Ground Subsystem

Ctrl

Positioning accuracies of one meter or less within 5 to 100 km of the controller station

KAIST LAD-GNSS
Test-bed Hardware Configuration

Pseudo-User

(Expanded)

73m

83m

KAIST LAD-GNSS IMT
Antenna & Receivers
(Existing)

16m

44m

46m

70m

79m
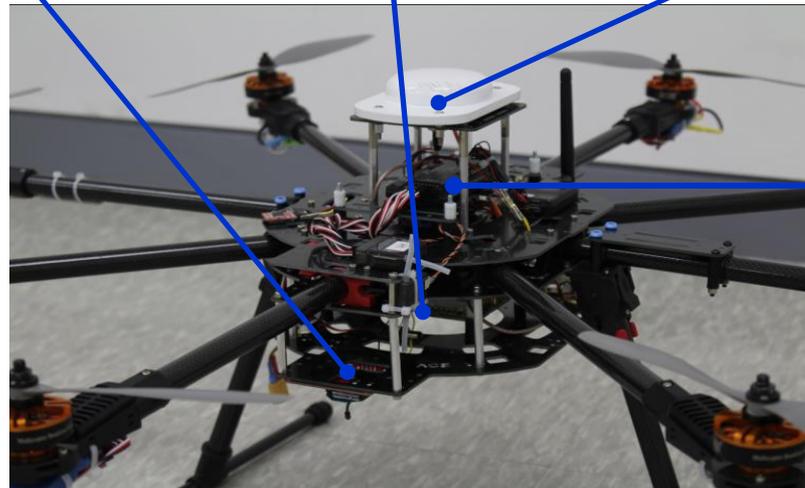
KAIST LAD-GNSS
Test-bed Hardware Configuration

**Modem
(Receive Differential
Correction)**
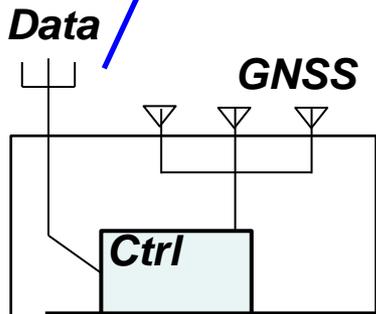
**Novatel
Receiver
(ProPak-V3)**

**Novatel
Antenna**

APM2.6 Controller

*Differential
Correction*
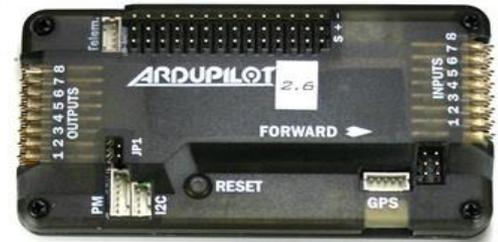
**Will be replaced
to Pixhawk**

Data

GNSS

*LAD-GNSS
Ground
Subsystem*

Ctrl

UAV Flight Testing:
LAD-GNSS vs. Standalone GPS

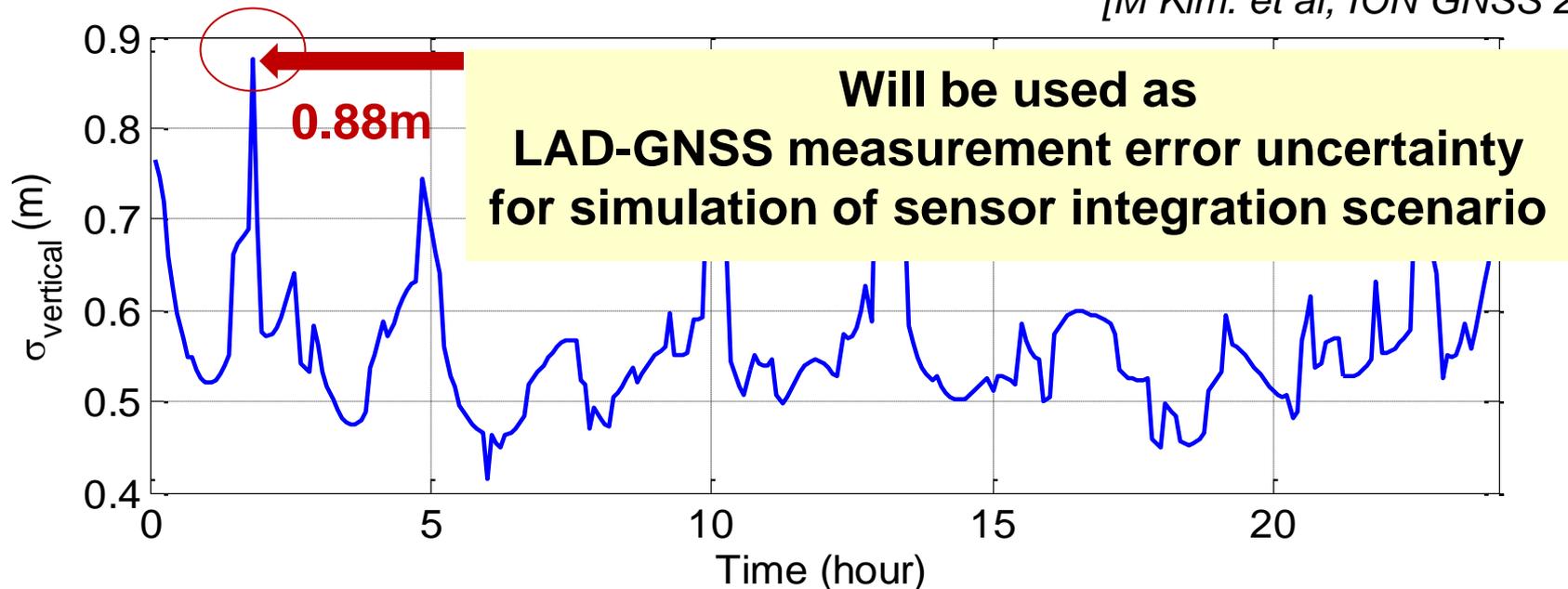LADGNSS
Performance Test using UAVs

0

Simulated σ_{vert} for UAV using LADGNSS error model

$$\sigma_i^2 = \sigma^2_{pr\_gnd,i} + \sigma^2_{tropo,i} + \sigma^2_{air,i} + \sigma^2_{iono,i}$$

	$\sigma^2_{pr\_gnd,i}$	$\sigma^2_{tropo,i}$	$\sigma^2_{air,i}$	$\sigma^2_{iono,i}$	Satellite constellation
Simulation Condition	GAD-B error model	Standard Residual Tropospheric Error Model of GBAS (60m from the ground)	AAD-A model	GBAS model	RTCA 24 Constellation Almanac

[M Kim. et al, ION GNSS 2014]

0.88m

Will be used as LAD-GNSS measurement error uncertainty for simulation of sensor integration scenario

- σ_{vert} for UAV is simulated during 24 hour applying LADGNSS error model

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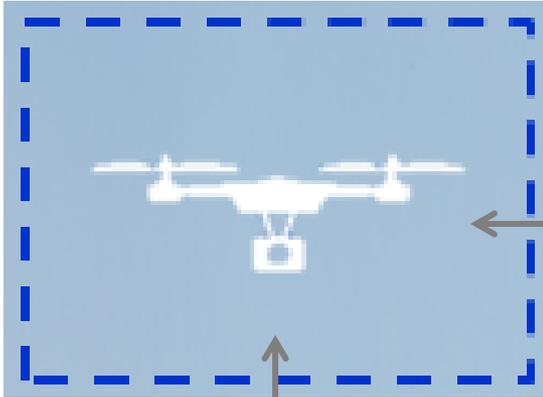
Navigation for UAV

Sensors used for UAV navigation

- GPS
- IMU sensors
- Barometer
- Magnetometer
- True airspeed
- Range finder (range to ground)
- Optical flow sensor
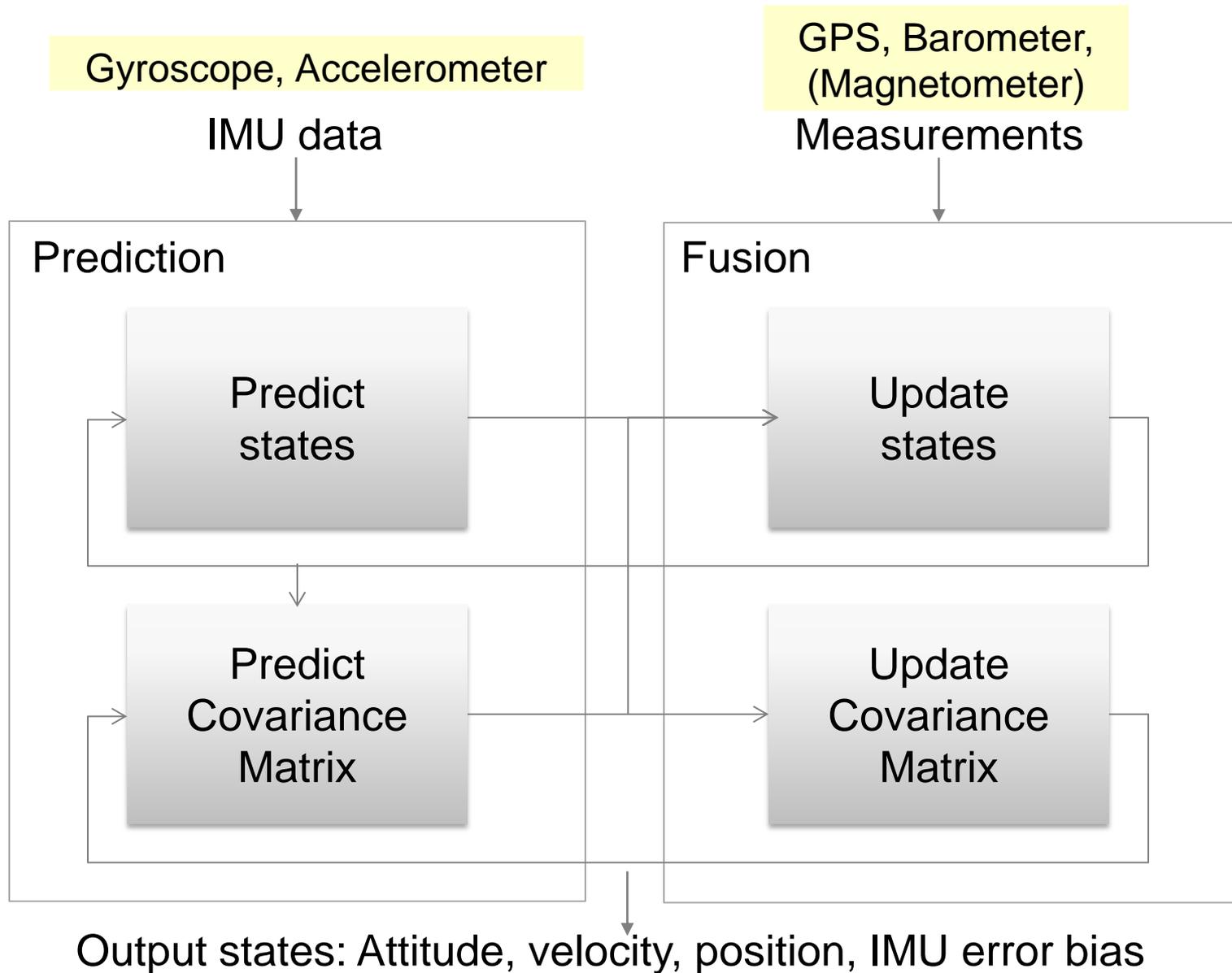 (optical and inertial sensor delta angles)

[Based on Pixhawk sensors]

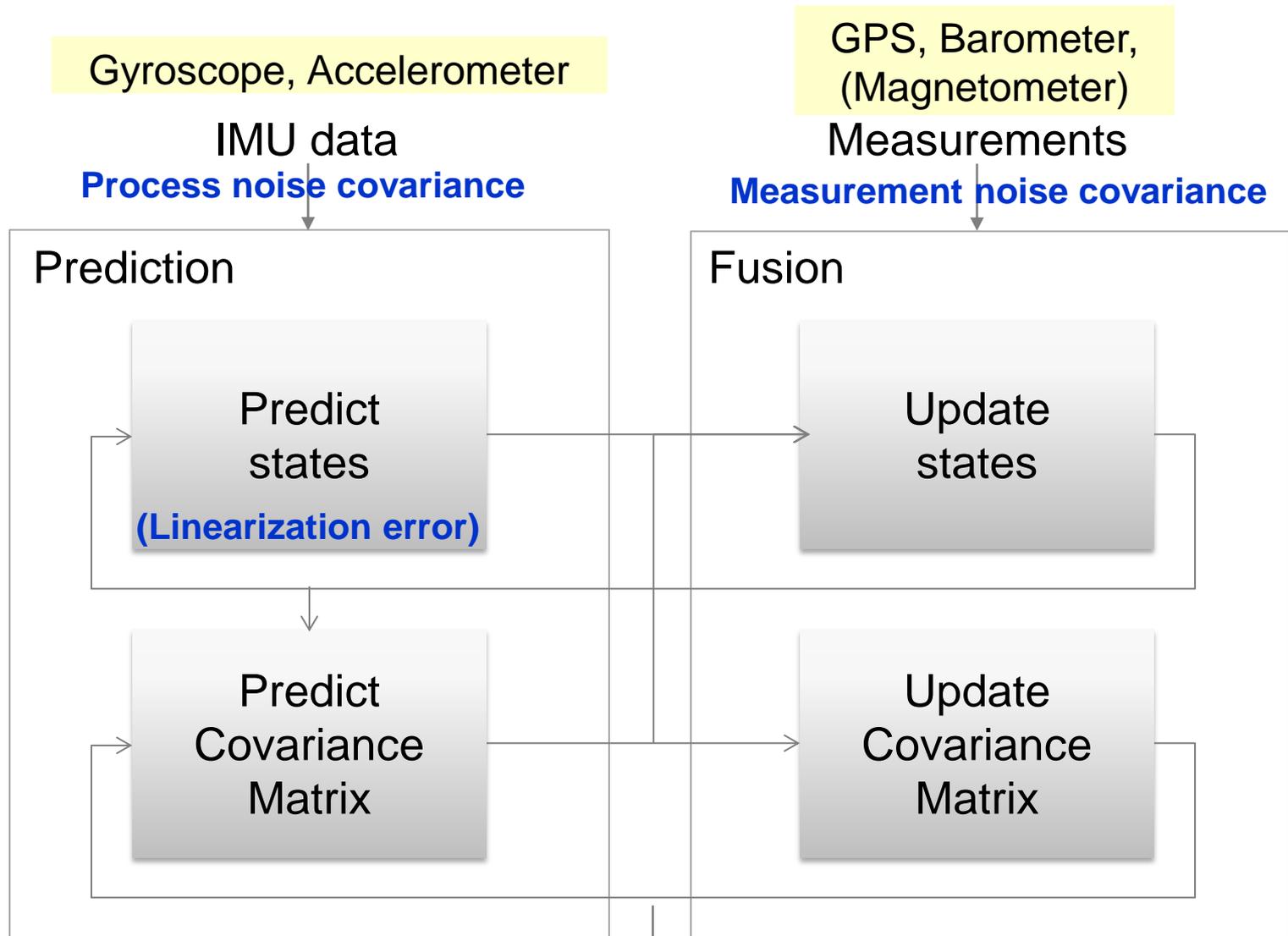## Algorithms used for UAV navigation

- Inertial navigation algorithm
- Extended Kalman Filter (EKF)   *[Pixhawk]*
- Unscented Kalman filter (UKF)
- Particle filter etc

Pixhawk EKF algorithm

Gyroscope, Accelerometer

GPS, Barometer,
(Magnetometer)

IMU data

Measurements

Prediction

Predict
states

Predict
Covariance
Matrix

Fusion

Update
states

Update
Covariance
Matrix

Output states: Attitude, velocity, position, IMU error bias

EKF covariance bounding

Gyroscope, Accelerometer

GPS, Barometer, (Magnetometer)

IMU data

Measurements

Process noise covariance

Measurement noise covariance

Prediction

Fusion

Predict states

(Linearization error)

Update states

Predict Covariance Matrix

Update Covariance Matrix

Output states: Attitude, velocity, position, IMU error bias *[Z, Xing, 2010]*

- IMU sensor bias model

$$b(t) = b_o + b_w(t) + b_1(t)$$ [D. GEBRE-EGZIABHER et al, 2003]

- IMU sensor bias modeling methods
  - b_o : Constant bias is continuously estimated by EKF

  - $b_w(t)$: sampling noise is modeled by white Gaussian noise

   Overbounded using CDF distribution to conservatively bound the white Gaussian noise

  - $b_1(t)$: Correlated.noise Modeled by gauss-Markov process with standard deviation and the time constant.

$$\dot{b}_1(t) = -\frac{1}{\tau}b_1(t) + w_{b_1}$$ Overbounded using autocorrelation plot [Z. Xing, 2010]

Example of modeling IMU sensor uncertainty
- Static gyroscope output

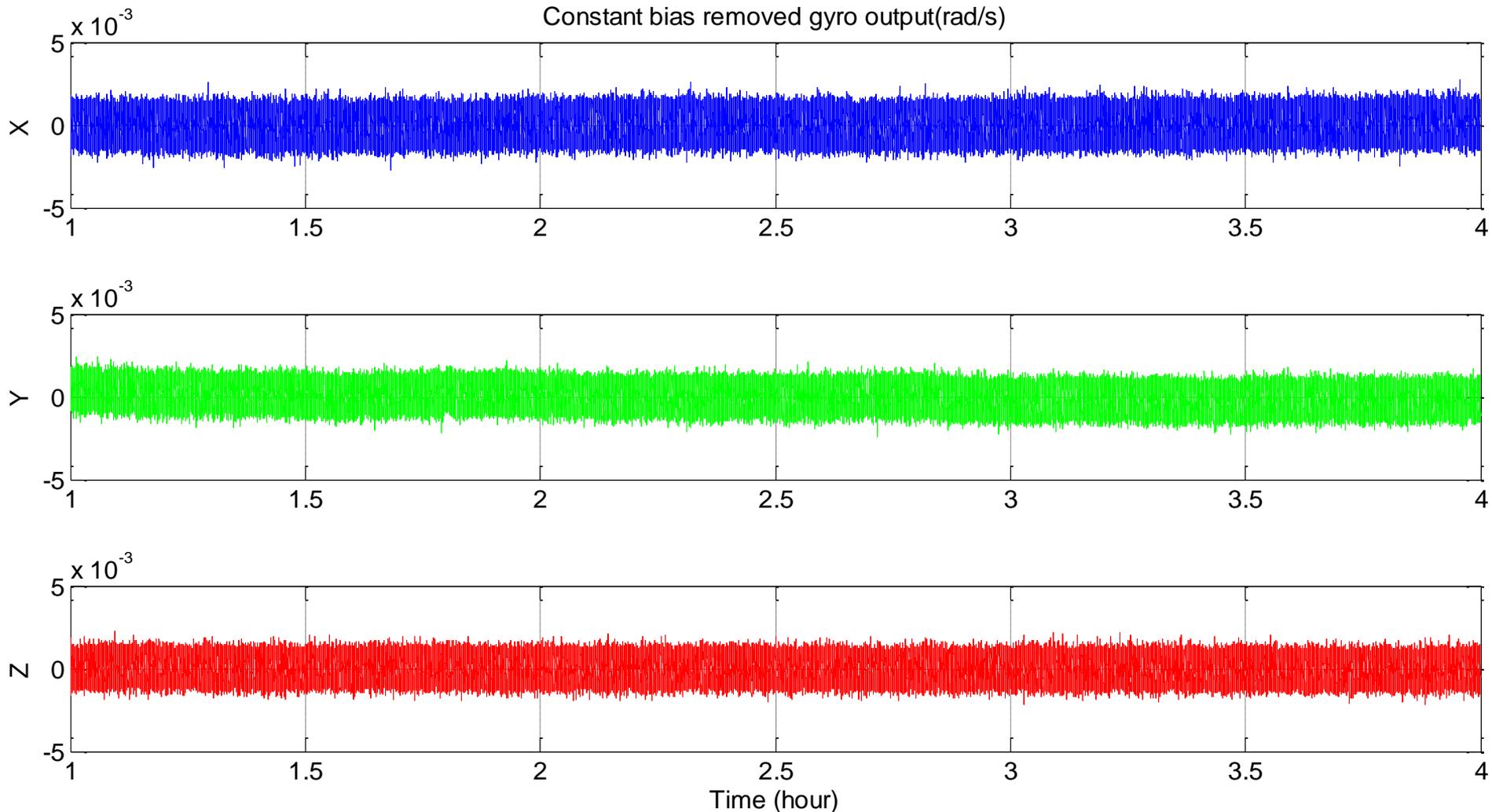- 100Hz gyroscope data collect for 4 hour in static condition from Pixhawk
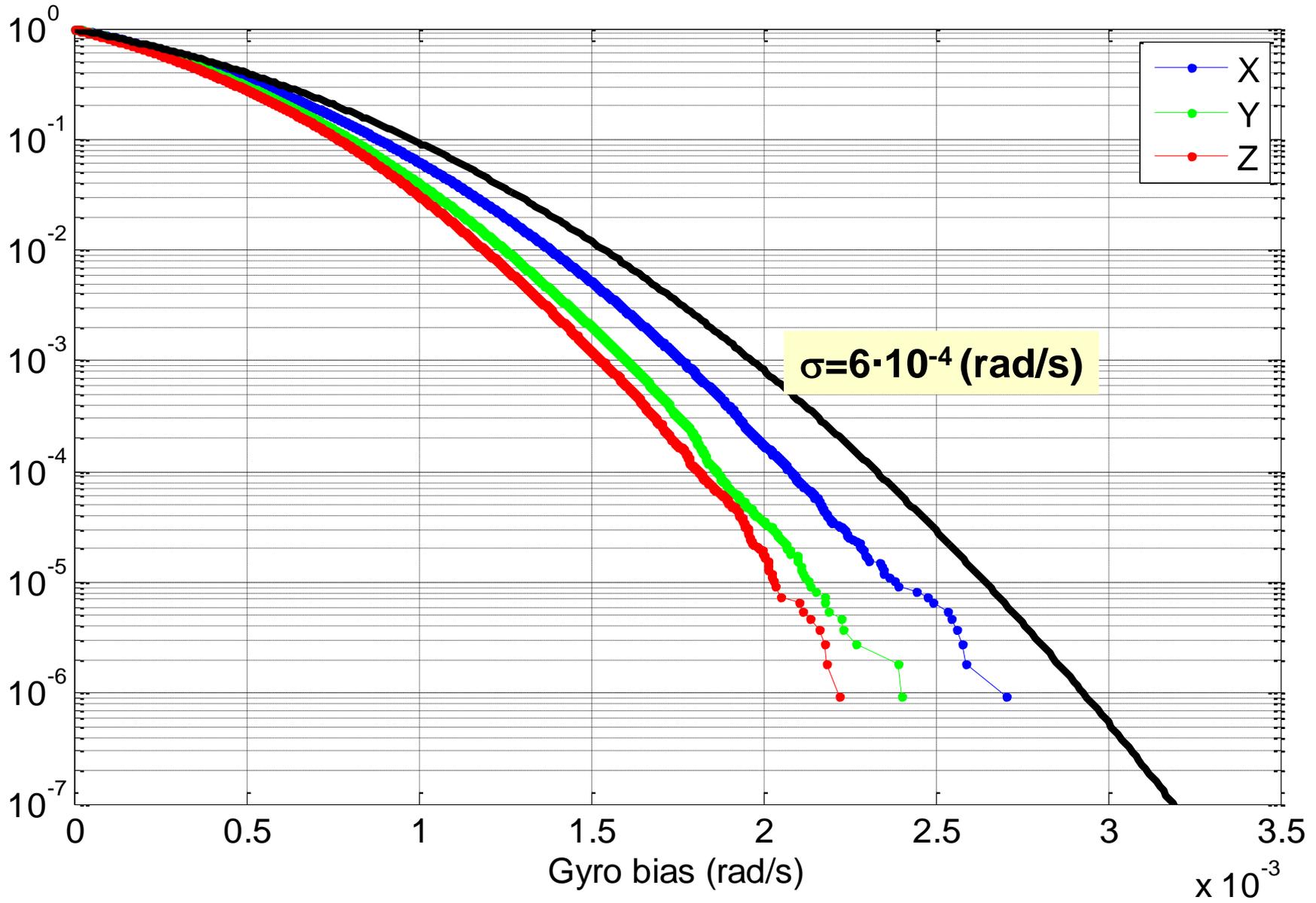

Gyro (rad/s)

Stable 3 hour dataset
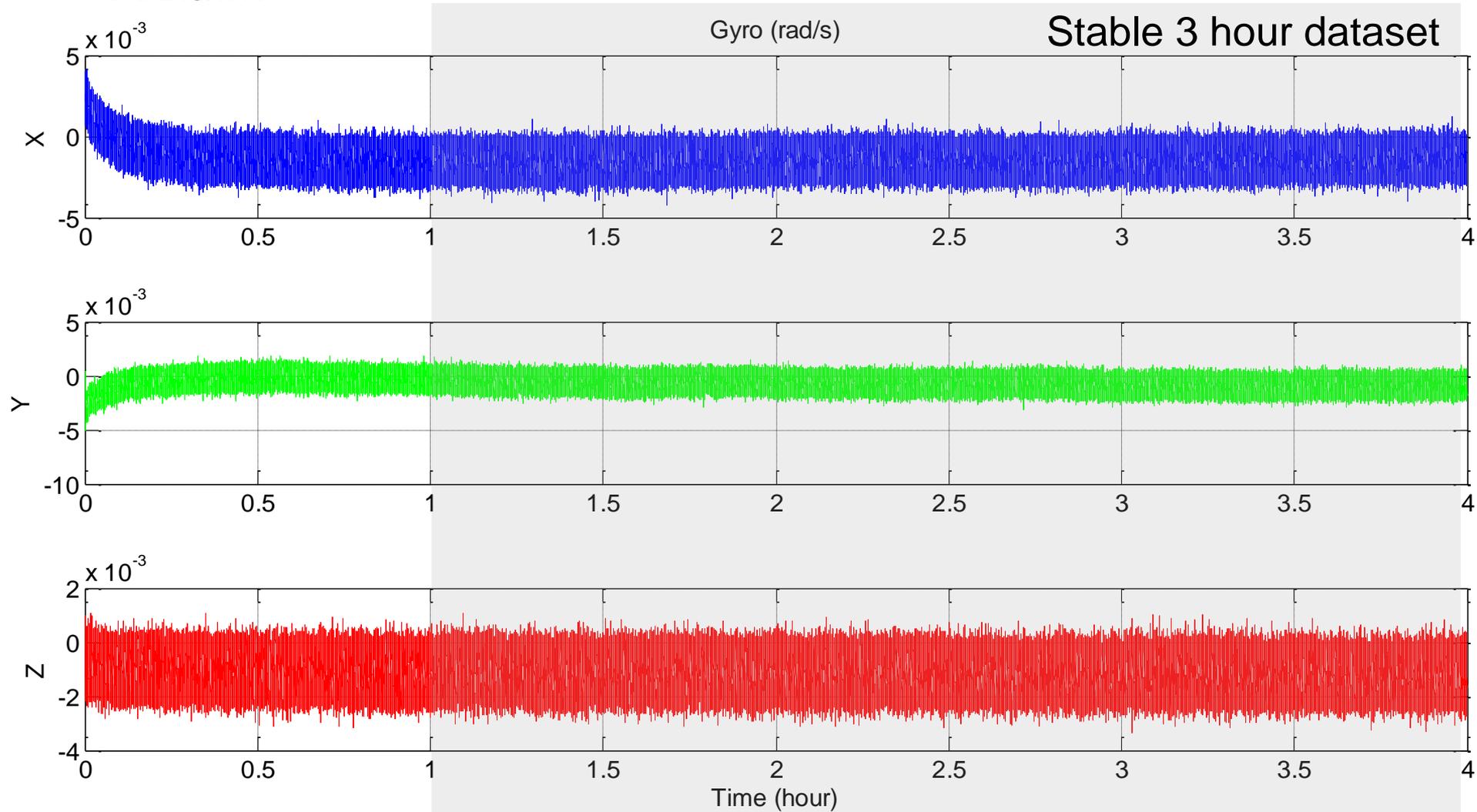
Example of modeling IMU sensor uncertainty
- Constant bias removal

- This constant bias term b_0 is continuously estimated with an additional states on EKF

Constant bias removed gyro output(rad/s)

Example of modeling IMU sensor uncertainty
- Wide band noise (Gyroscope)

σ=6·10⁻⁴ (rad/s)

Example of modeling IMU sensor uncertainty
- Correlated noise (Gyroscope)

$$R_x(\tau) = \sigma^2 e^{-|\tau|/\tau_{corr}}$$

$\sigma = 1.6 \cdot 10^{-4}$ (rad/s)
$\tau = 3000$s
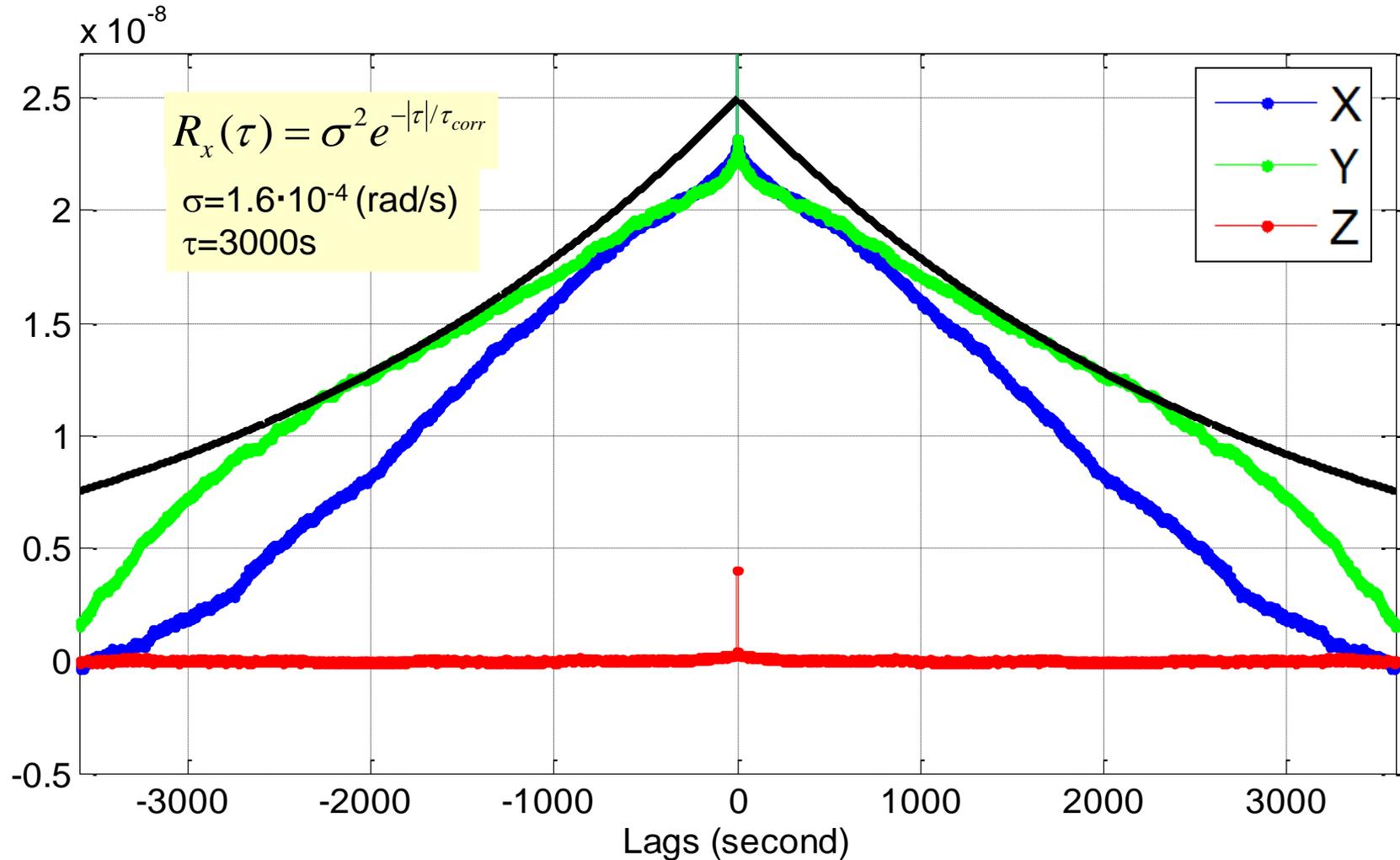
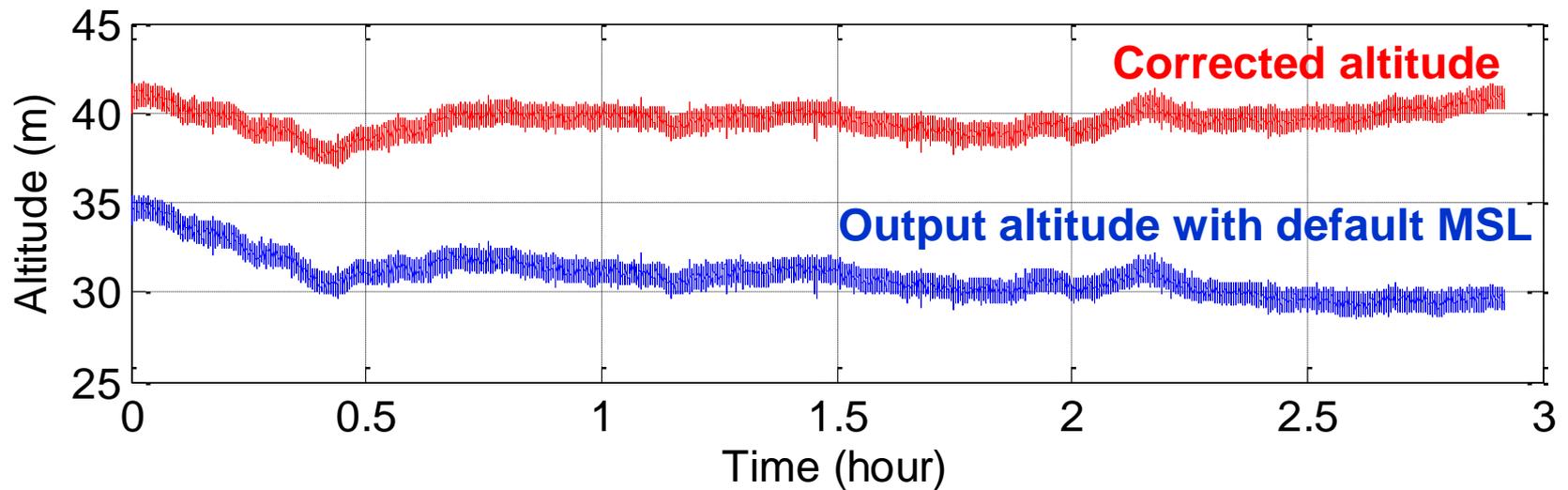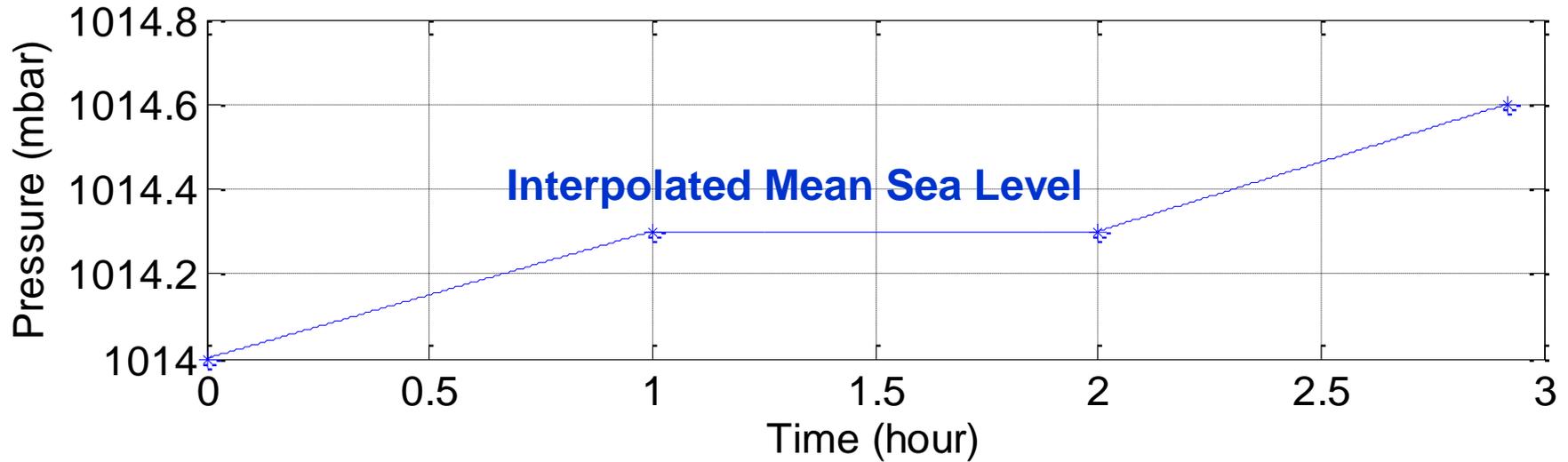*[J. Rife, 2007 ; Z. Xing, 2010]*

Find the exponential autocorrelation plot with variance and correlation time which overbound actual data-driven autocorrelation plot (averaged every 1 sec)

Barometer sensor error

GPS altitude from Pixhawk Ublox GPS receiver

Surveyed Position

Corrected altitude with pressure information from nearest airports
[NOAA aviation weather center]

Altitude with default Mean Sea level reference (1013.25hPa) set by Pixhawk
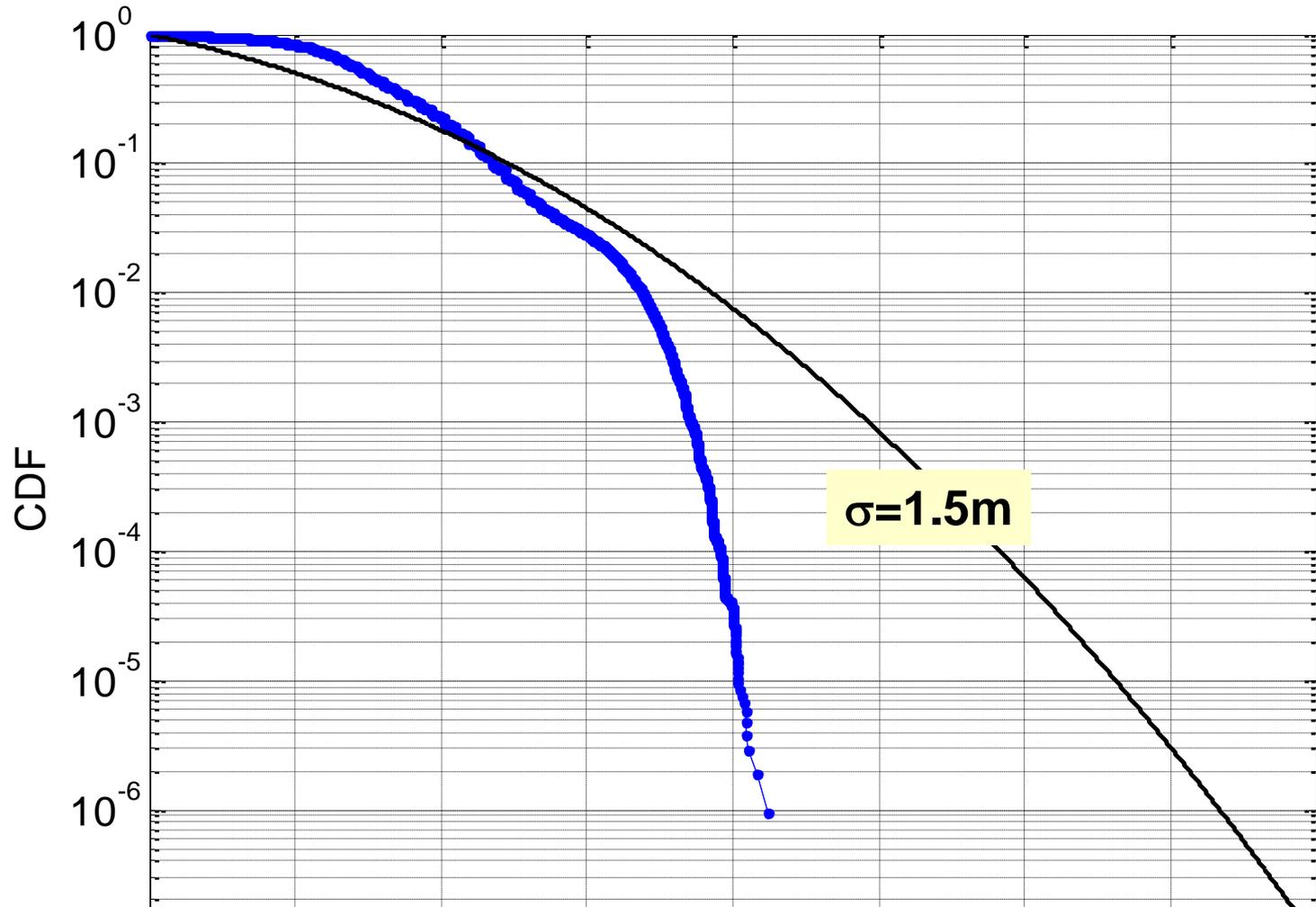
Altitude (m)

Time (hour)
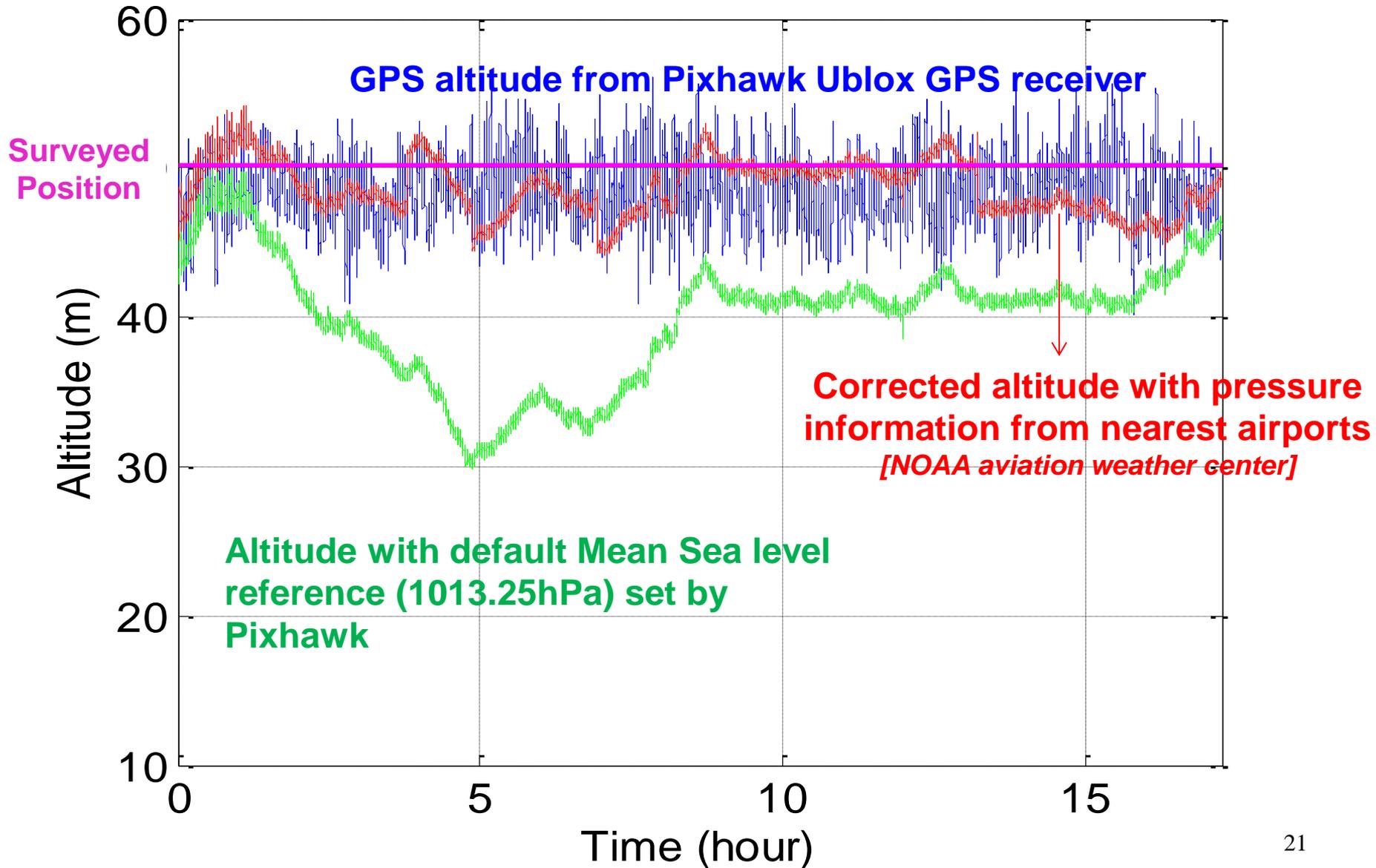
Barometer error bounding
Drift compensation

# Barometer altitude error bounding

σ=1.5m

Many approaches for barometer drift compensation could be considered. Further studies will be conducted for our UAV test

Simulation results using overbounded error noise covariance

Simulation Condition (bounded noise covariance)	IMU sensor (prediction) – <u>static situation</u>		Measurement sensor (update)		
	Acc	Gyro	Stand-alone GPS	Barometer	LAD-GNSS
	$\sigma_w=1.5^*\cdot10^{-2}$ (m/s/s) $\sigma_{b1}=3.7\cdot10^{-3}$ (m/s/s) $\tau=3300s$	$\sigma_w=6\cdot10^{-4}$ (rad/s) $\sigma_{b1}=1.6\cdot10^{-4}$ (rad/s) $\tau=3000s$	7.5m *[spsps2008]*	1.5m	0.88m (max over 24 hours)

* Simulation is performed by modifying the EKF filter algorithm used by Pixhawk

error bound=$K_{ffmd}\cdot\sigma_{overbounded}$

Stand-alone GPS

Barometer
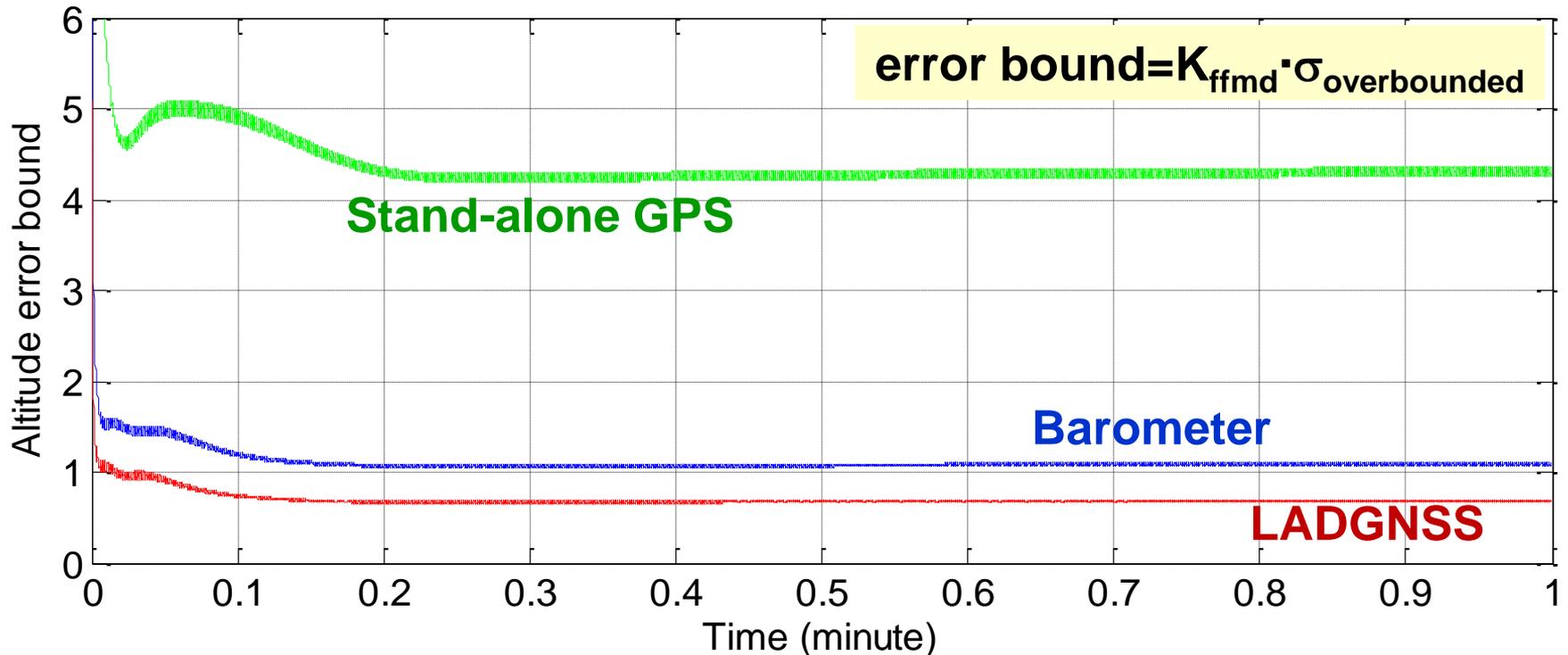
LADGNSS

Conclusion

- **LADGNSS error models for UAVs has been developed, and UAV flight tests have been performed using differential corrections from LADGNSS test-bed at KAIST**

- **Both process noise and measurement noise uncertainties of integrated sensors were estimated and overbounded to simulate vertical position error bounds**
  - **LADGNSS when combined with IMU sensor reduced vertical position error bounds significantly compared to stand-alone GPS or barometer**

- **In this study, we derived sensor error models under static conditions and assumed linear state transition for state covariance bounding**
  - **Future work is needed: bounding non-linearities in the state transition matrix, error modeling in dynamic scenarios and experimental flight-test validation**

Thank you

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