

Optimal Attitude Estimation Using Measurement Covariance Based on U.K.F

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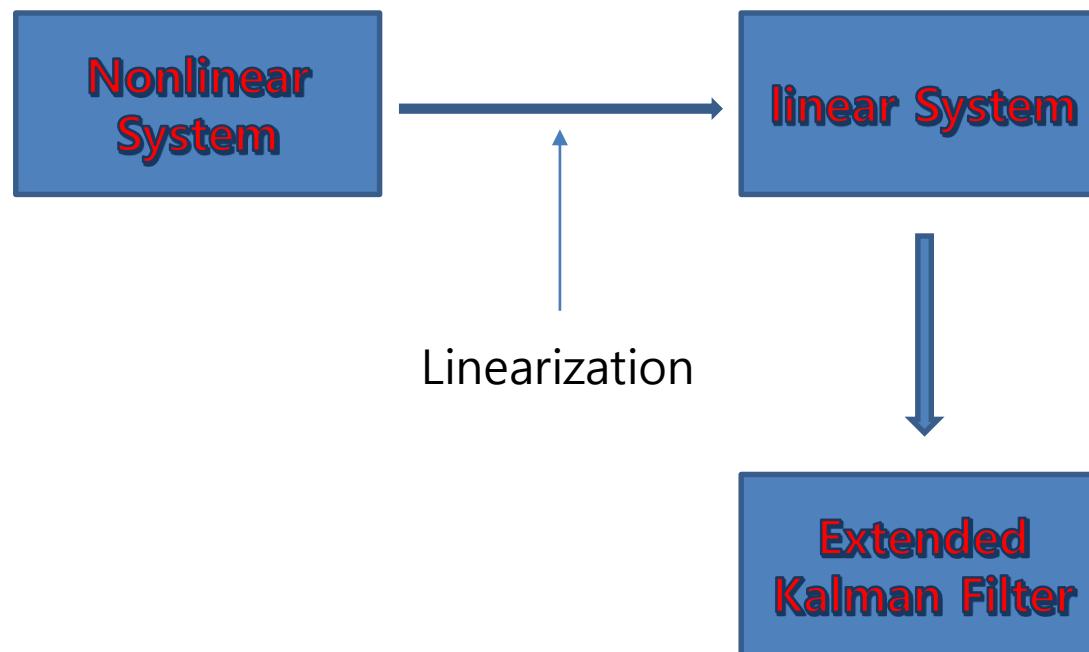
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I Introduction

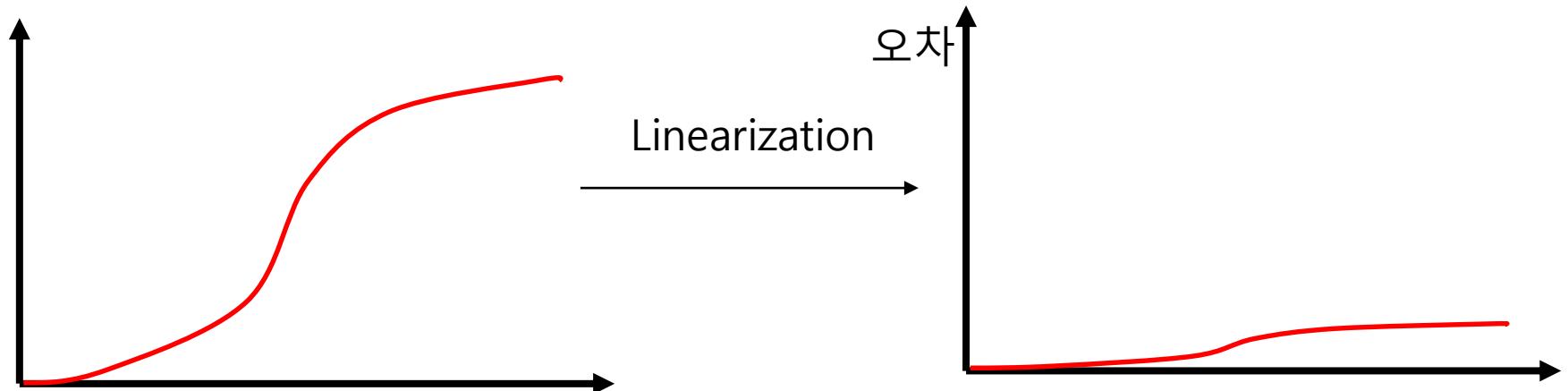
Research purpose



I Introduction

Research purpose

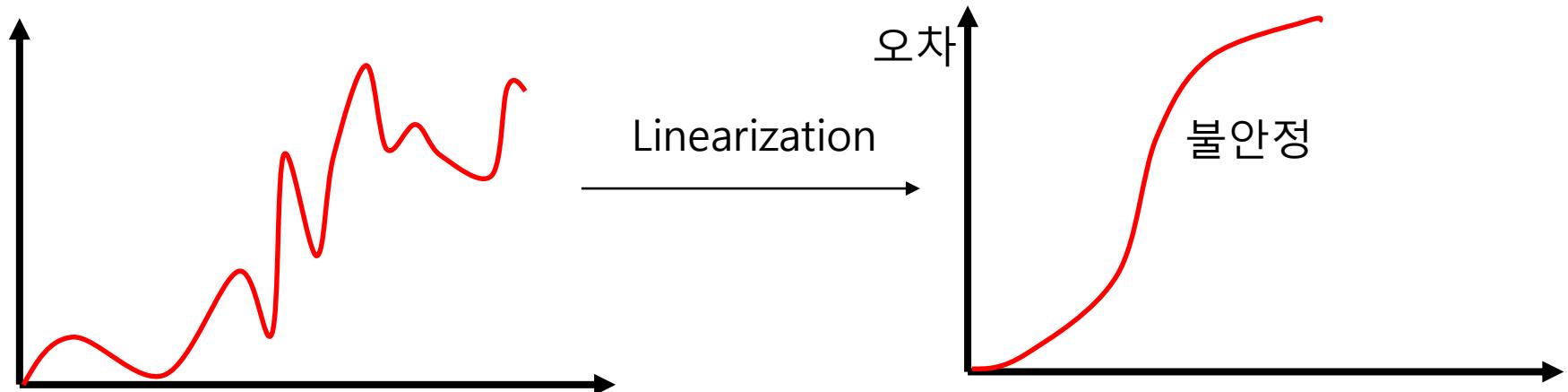
Nonlinear System



I Introduction

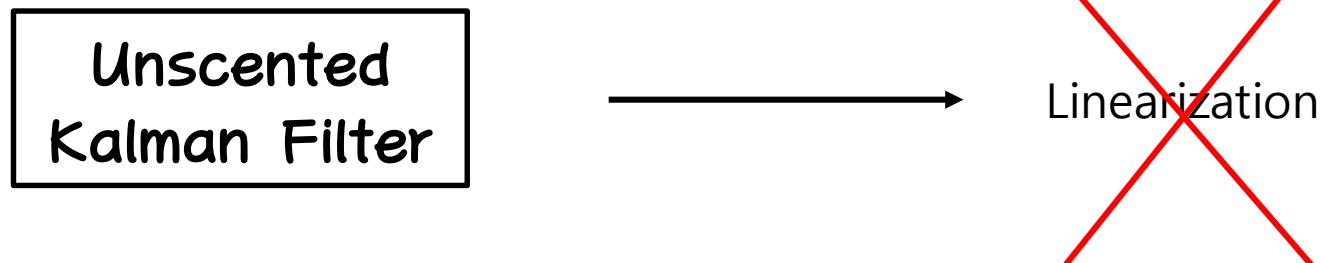
Research purpose

Nonlinear System



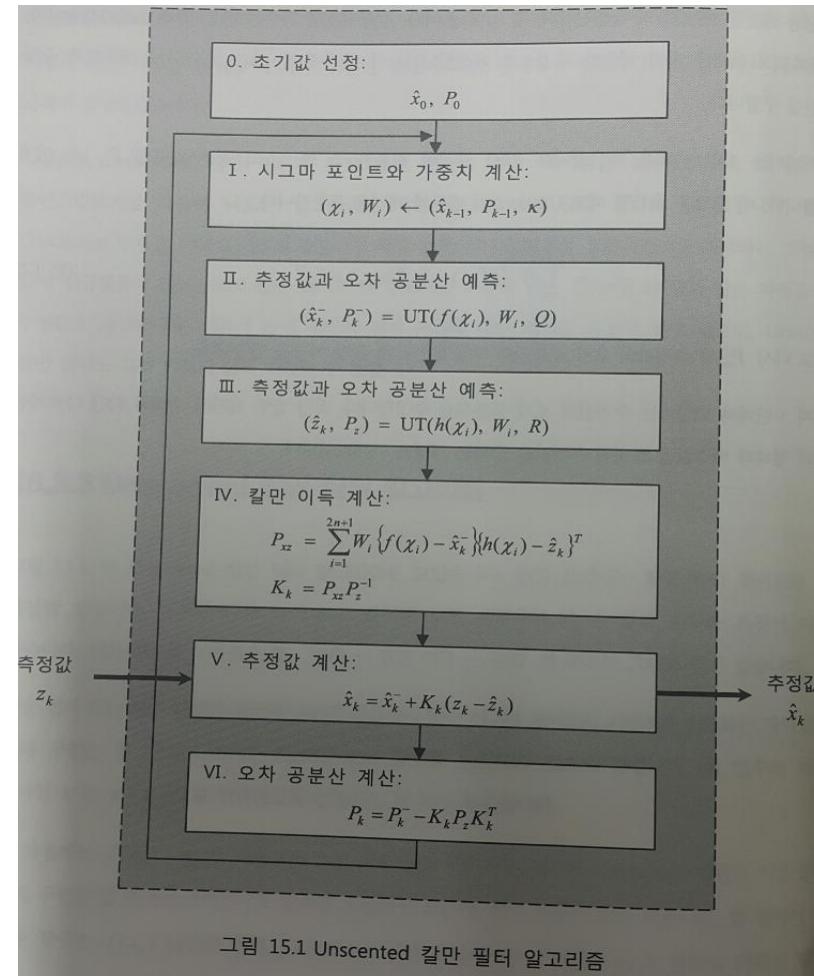
I Introduction

Research purpose



II Algorithm

Unscented Kalman Filter



II Algorithm

Unscented Kalman Filter

$$\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k, k) + G_k \mathbf{w}_k$$

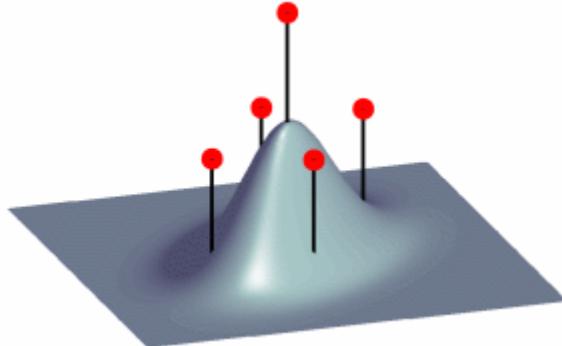
$$\tilde{\mathbf{y}}_k = \mathbf{h}(\mathbf{x}_k, k) + \mathbf{v}_k$$

1. 시그마 포인트와 가중치 계산

$$\sigma_k \leftarrow 2n \text{ columns from } \pm \sqrt{(n + \lambda)[P_k^+ + \bar{Q}_k]}$$

$$\chi_k(0) = \hat{\mathbf{x}}_k^+$$

$$\chi_k(i) = \sigma_k(i) + \hat{\mathbf{x}}_k^+$$



$$\chi_{k+1}(i) = \mathbf{f}[\chi_k(i), k]$$

II Algorithm

Unscented Kalman Filter

2. 추정값과 오차 공분산 예측

$$\hat{\mathbf{x}}_{k+1}^- = \frac{1}{n + \lambda} \left\{ \lambda \boldsymbol{\chi}_{k+1}(0) + \frac{1}{2} \sum_{i=1}^{2n} \boldsymbol{\chi}_{k+1}(i) \right\}$$

$$\begin{aligned} P_{k+1}^- = & \frac{1}{n + \lambda} \left\{ \lambda [\boldsymbol{\chi}_{k+1}(0) - \hat{\mathbf{x}}_{k+1}^-] [\boldsymbol{\chi}_{k+1}(0) - \hat{\mathbf{x}}_{k+1}^-]^T \right. \\ & \left. + \frac{1}{2} \sum_{i=1}^{2n} [\boldsymbol{\chi}_{k+1}(i) - \hat{\mathbf{x}}_{k+1}^-] [\boldsymbol{\chi}_{k+1}(i) - \hat{\mathbf{x}}_{k+1}^-]^T \right\} + \bar{Q}_k \end{aligned}$$

II Algorithm

Unscented Kalman Filter

3. 측정값과 오차 공분산 예측

$$\gamma_{k+1}(i) = \mathbf{h}[\chi_{k+1}(i), k]$$

$$\hat{\mathbf{y}}_{k+1}^- = \frac{1}{n + \lambda} \left\{ \lambda \gamma_{k+1}(0) + \frac{1}{2} \sum_{i=1}^{2n} \gamma_{k+1}(i) \right\}$$

$$\begin{aligned} P_{k+1}^{yy} &= \frac{1}{n + \lambda} \left\{ \lambda [\gamma_{k+1}(0) - \hat{\mathbf{y}}_{k+1}^-] [\gamma_{k+1}(0) - \hat{\mathbf{y}}_{k+1}^-]^T \right. \\ &\quad \left. + \frac{1}{2} \sum_{i=1}^{2n} [\gamma_{k+1}(i) - \hat{\mathbf{y}}_{k+1}^-] [\gamma_{k+1}(i) - \hat{\mathbf{y}}_{k+1}^-]^T \right\} \\ P_{k+1}^{vv} &= P_{k+1}^{yy} + R_{k+1} \end{aligned}$$

II Algorithm

Unscented Kalman Filter

3. 측정값과 오차 공분산 예측

$$\begin{aligned} P_{k+1}^{xy} = & \frac{1}{n + \lambda} \left\{ \lambda [\chi_{k+1}(0) - \hat{x}_{k+1}^-] [\gamma_{k+1}(0) - \hat{y}_{k+1}^-]^T \right. \\ & \left. + \frac{1}{2} \sum_{i=1}^{2n} [\chi_{k+1}(i) - \hat{x}_{k+1}^-] [\gamma_{k+1}(i) - \hat{y}_{k+1}^-]^T \right\} \end{aligned}$$

II Algorithm

Unscented Kalman Filter

4. 칼만 이득 계산

$$K_k = P_k^{xy} (P_k^{vv})^{-1}$$

5. 추정값 계산

$$\mathbf{v}_k \equiv \tilde{\mathbf{y}}_k - \hat{\mathbf{y}}_k^- = \tilde{\mathbf{y}}_k - \mathbf{h}(\hat{\mathbf{x}}_k^-, k)$$

$$\hat{\mathbf{x}}_k^+ = \hat{\mathbf{x}}_k^- + K_k \mathbf{v}_k$$

6. 오차 공분산 계산

$$P_k^+ = P_k^- - K_k P_k^{vv} K_k^T$$

III Simulation & Result

Simulation A

State : Attitude error & bias

State Update : Gyro

Measurement : Accelerometer & Magnetometer

Filter : Unscented Kalman Filter

Simulation B

State : Attitude error & bias

State Update : Gyro

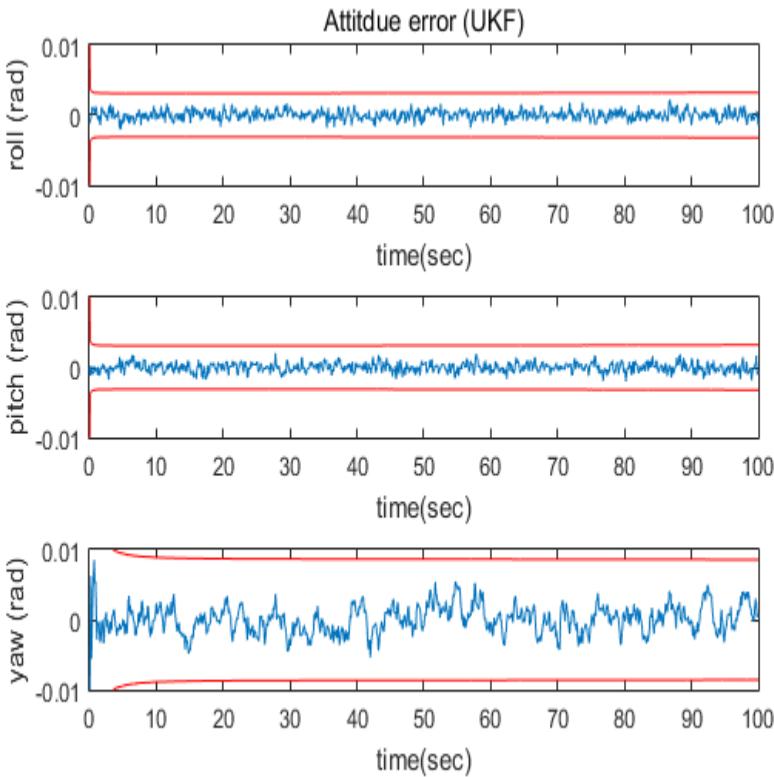
Measurement : Accelerometer & Magnetometer

Filter : Extended Kalman Filter

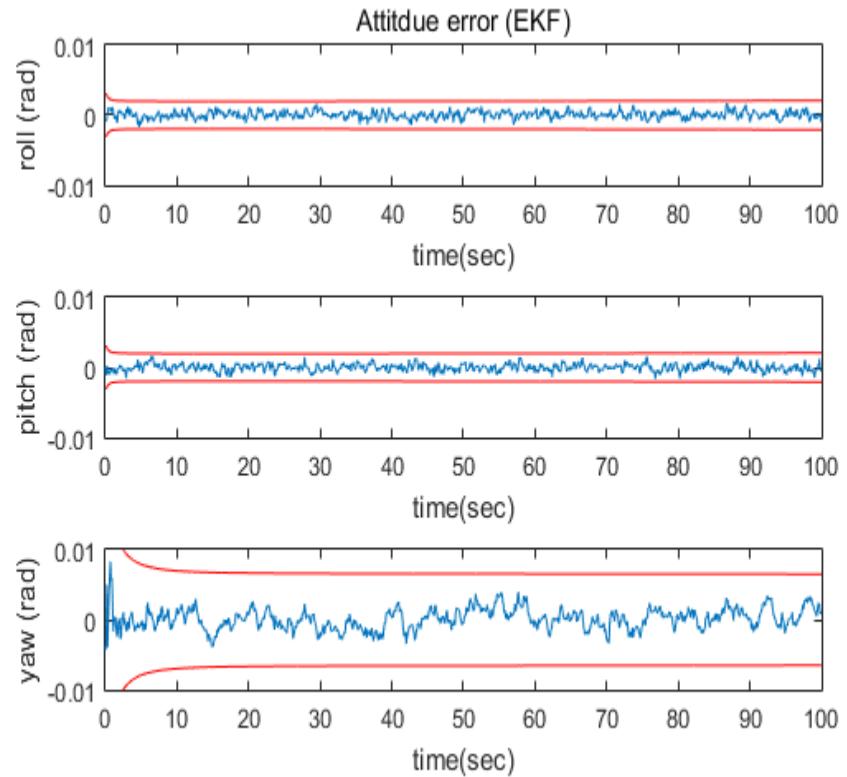
III Simulation & Result

Attitude Error

Simulation A



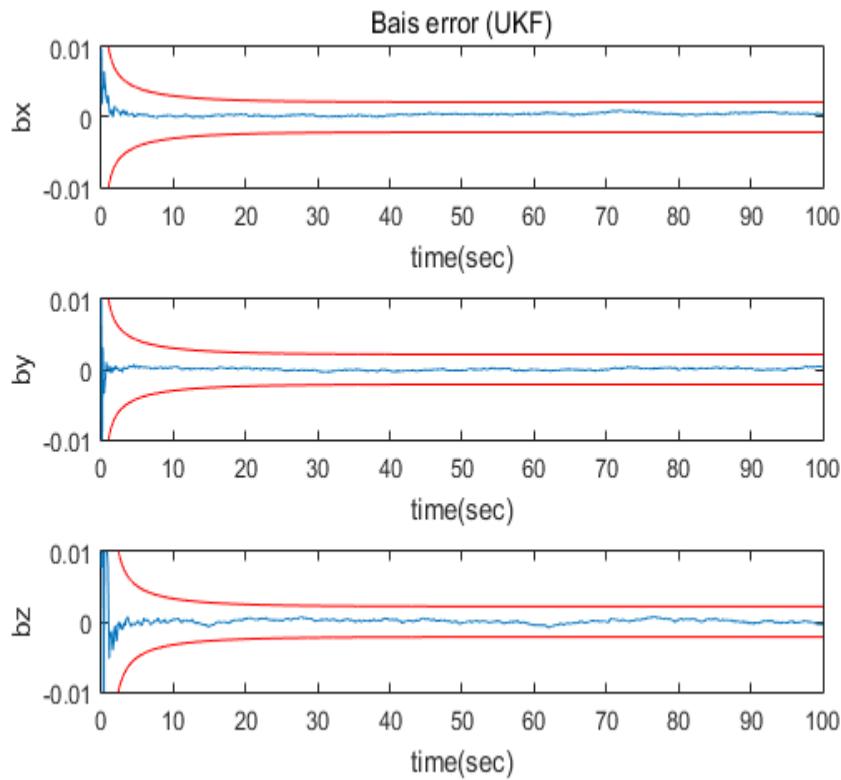
Simulation B



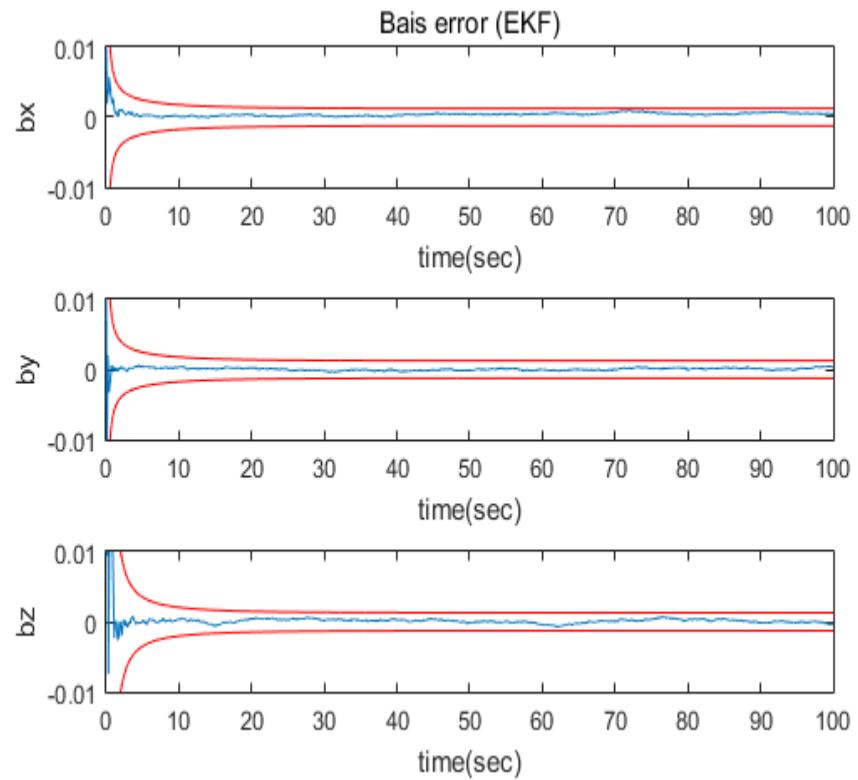
III Simulation & Result

Bias Error

Simulation A



Simulation B



III Simulation & Result

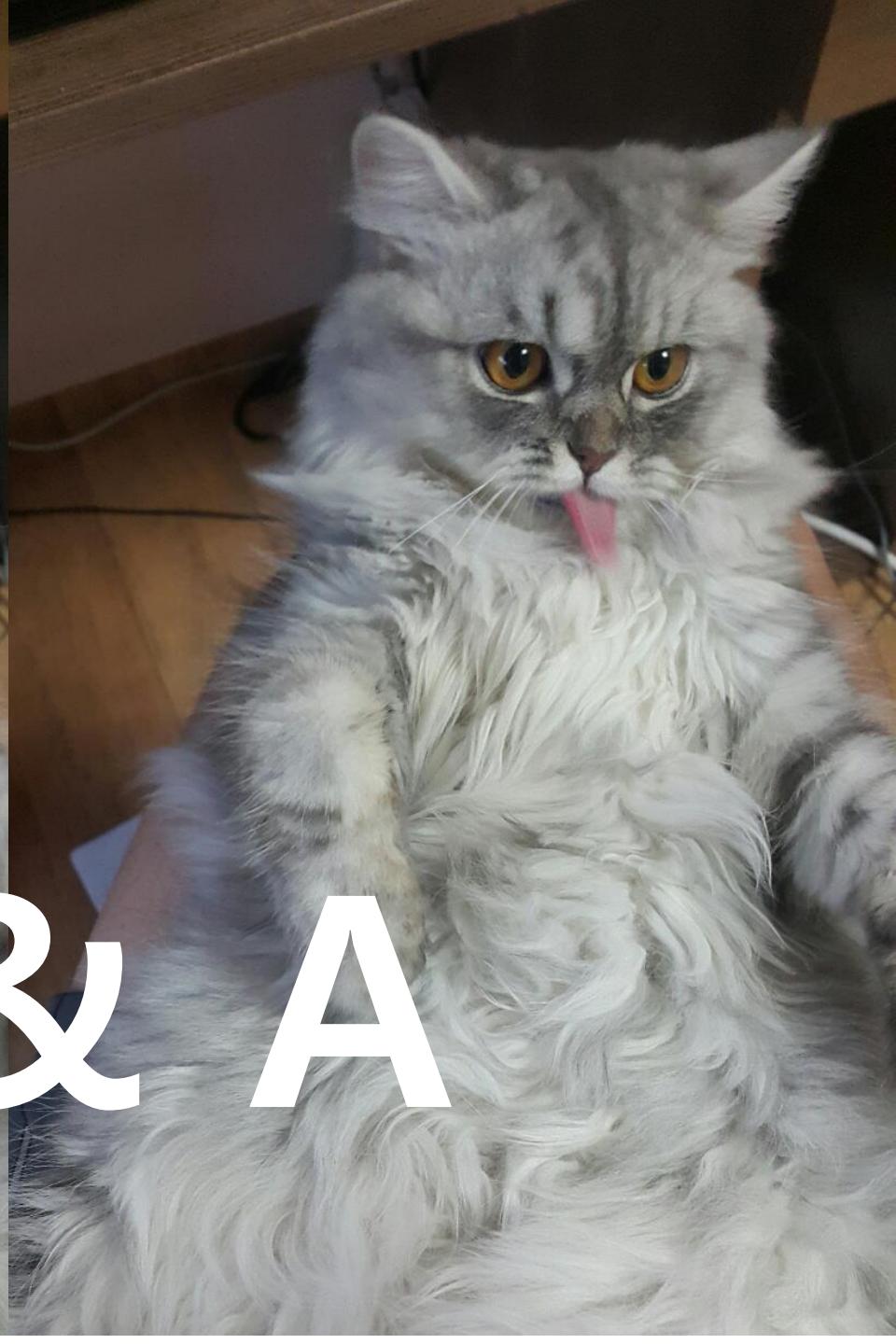
Result

1. 자세와 바이어스를 UKF와 EKF를 통해 비교했다.
2. 비선형성이 크지 않아 그렇게 두 필터의 오차가 비슷하게 나타났다.
3. 진동상황을 추가하면 UKF가 더 좋은 성능을 보일것이라 예상된다.

IV Future Plan

Next Seminar

1. Unscented Kalman Filter
2. Particle Filter



Q & A