

## Part 1

### Visual Pose Estimation

This part is in 'pred\_step' and 'upd\_step':

#### Step1. Process Model

Define parameters:

$$\alpha = 0.25, \beta = 2, k = 3, g = [-0.23, -0.19, -9.829]$$

$$\lambda = \alpha^2(n + k) - n$$

Build the process model as the same as part1:

$$R(q) = \begin{bmatrix} \cos\theta\cos\varphi & \sin\psi\sin\theta\cos\varphi - \cos\psi\sin\varphi & \cos\psi\sin\theta\cos\varphi + \sin\psi\sin\varphi \\ \cos\theta\sin\varphi & \sin\psi\sin\theta\sin\varphi + \cos\psi\cos\varphi & \cos\psi\sin\theta\sin\varphi - \sin\psi\cos\varphi \\ -\sin\varphi & \sin\psi\cos\theta & \cos\psi\cos\theta \end{bmatrix}$$

$$G(q) = \begin{bmatrix} \cos\varphi\cos\theta & -\sin\theta & 0 \\ \cos\varphi\sin\theta & \cos\theta & 0 \\ -\sin\varphi & 0 & 1 \end{bmatrix}$$

$$\dot{x} = \begin{bmatrix} x_3 \\ G(x_2)^{-1}(\omega_m - x_4 - n_g) \\ R(q)(a_m - x_5 - n_a) \\ n_{bg} \\ n_{ba} \end{bmatrix} = f$$

#### Step2. Compute Sigma Points

We use methods below to get sigma points:

Cholesky decomposition

$$S = \sqrt{\lambda + n} * \text{chol}(\Sigma_{t-1}), \quad W = [S, -S]$$

$$X_{aug} = \mu_{aug} + W$$

#### Step3. Propagate Sigma Points and Compute mean & covariance

$$X_t = f(X_{aug}, \mu_{aug})$$

$$\bar{\mu}_t = \sum_{i=0}^{2n'} W_i^{(m)} \chi_t^{(i)} \quad \bar{\Sigma}_t = \sum_{i=0}^{2n'} W_i^{(c)} (\chi_t^{(i)} - \bar{\mu}_t)(\chi_t^{(i)} - \bar{\mu}_t)^T$$

#### Step4. Update Step

##### 1. Assumptions and Linearization

The process is also not complex.

Because our Observation Model is simple. We can directly get that

$C_t$  is a  $6 \times 15$  identity matrix  $W_t$  is a  $6 \times 6$  identity matrix.

##### 2. Update Step

$$K_t = \bar{\Sigma}_t C_t^T (C_t \bar{\Sigma}_t C_t^T + W_t R_t W_t^T)^{-1}$$

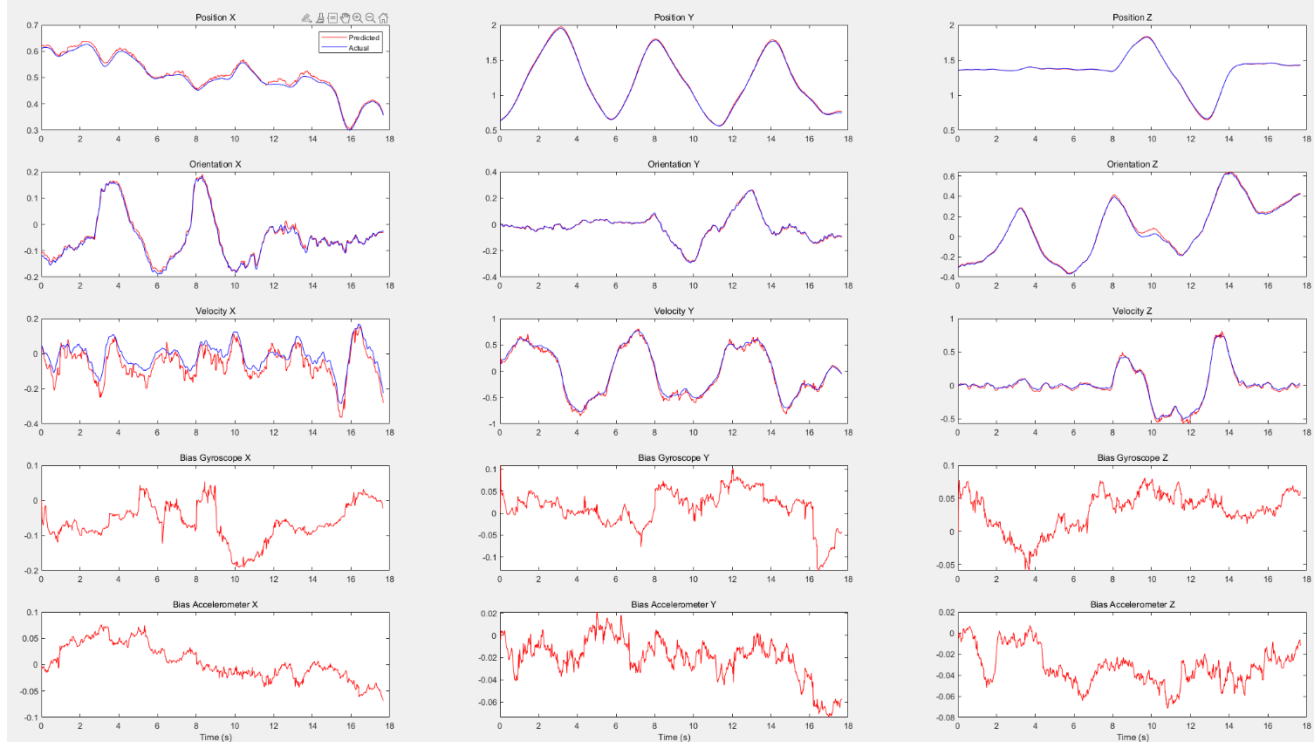
$$\mu_t = \bar{\mu}_t + K_t C_t \bar{\Sigma}_t$$

$$\Sigma_t = \bar{\Sigma}_t - K_t (z_t - g(\bar{\mu}_t, 0))$$

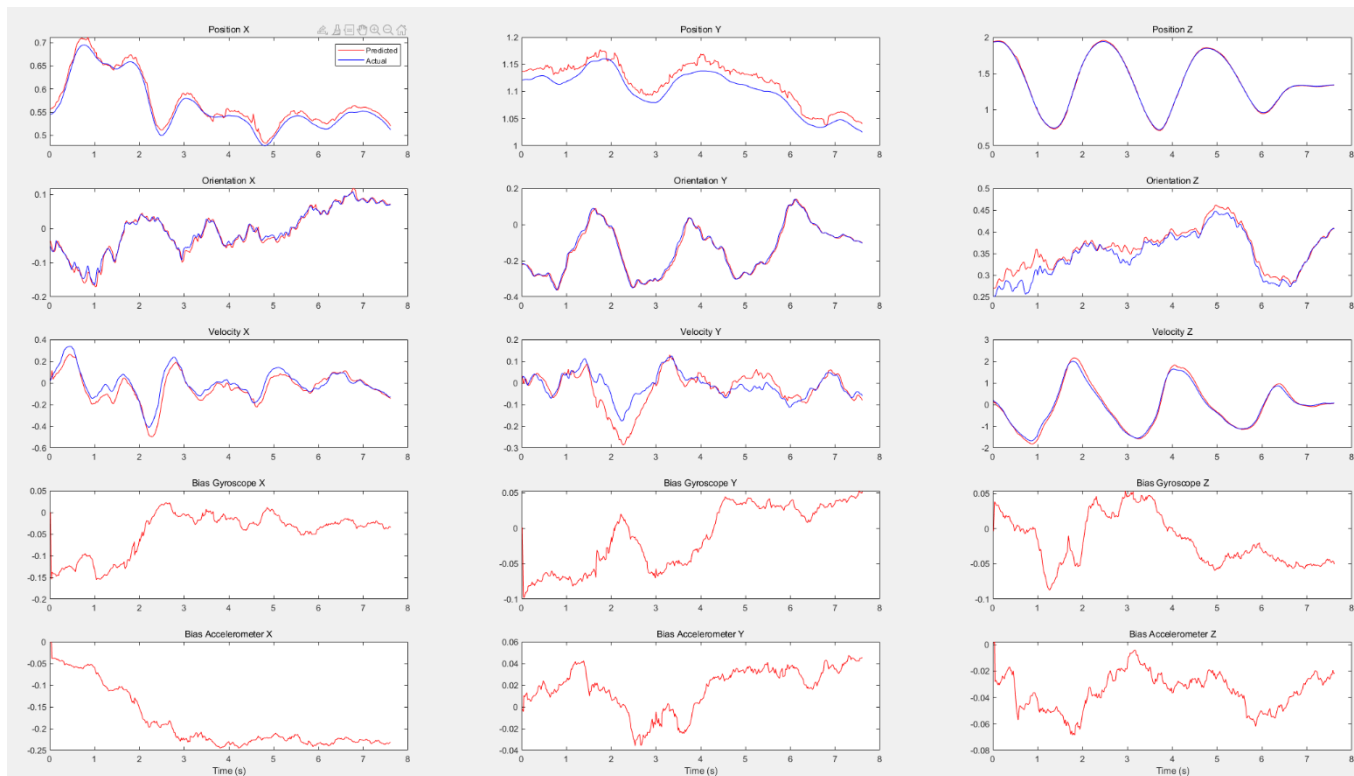
**$K_t$  is the Kalman-gain.** The Kalman-gain is the weight given to the measurements and current-state estimate, and can be "tuned" to achieve a particular performance. With a high-gain, the filter places more weight on the most recent measurements, and thus conforms to them more responsively.

Plotting results:

## Datasheet 1:



## Datasheet 4:



## Part 2

### Prediction Step

This part is the same with part1.

### Update Step

#### Step1. Measurement Model

Build the nonlinear model:

$$Z = g(x_t, v_t) = Adjoint * [x_3; w_b]$$
$$Adjoint = \begin{bmatrix} R_c^b & -R_c^b * \widehat{r_{bc}} \\ 0 & R_c^b \end{bmatrix}$$

#### Step2. Compute Sigma Points

We use methods below to get sigma points:

Cholesky decomposition

$$S = \sqrt{\lambda + n} * chol(\Sigma_{t-1}), \quad W = [S, -S]$$
$$X_{aug} = \mu_{aug} + W$$

#### Step3. Propagate Sigma Points and Compute mean & covariance

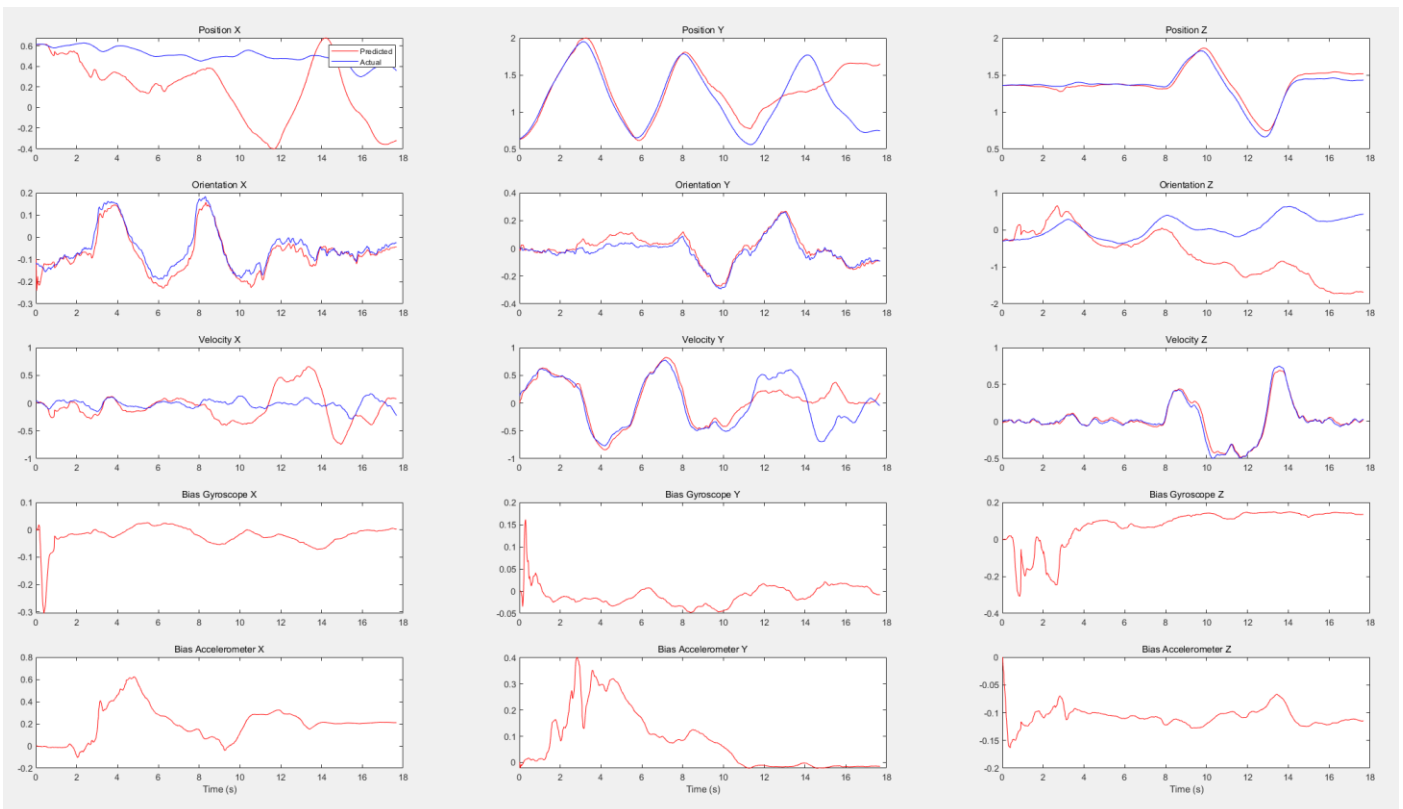
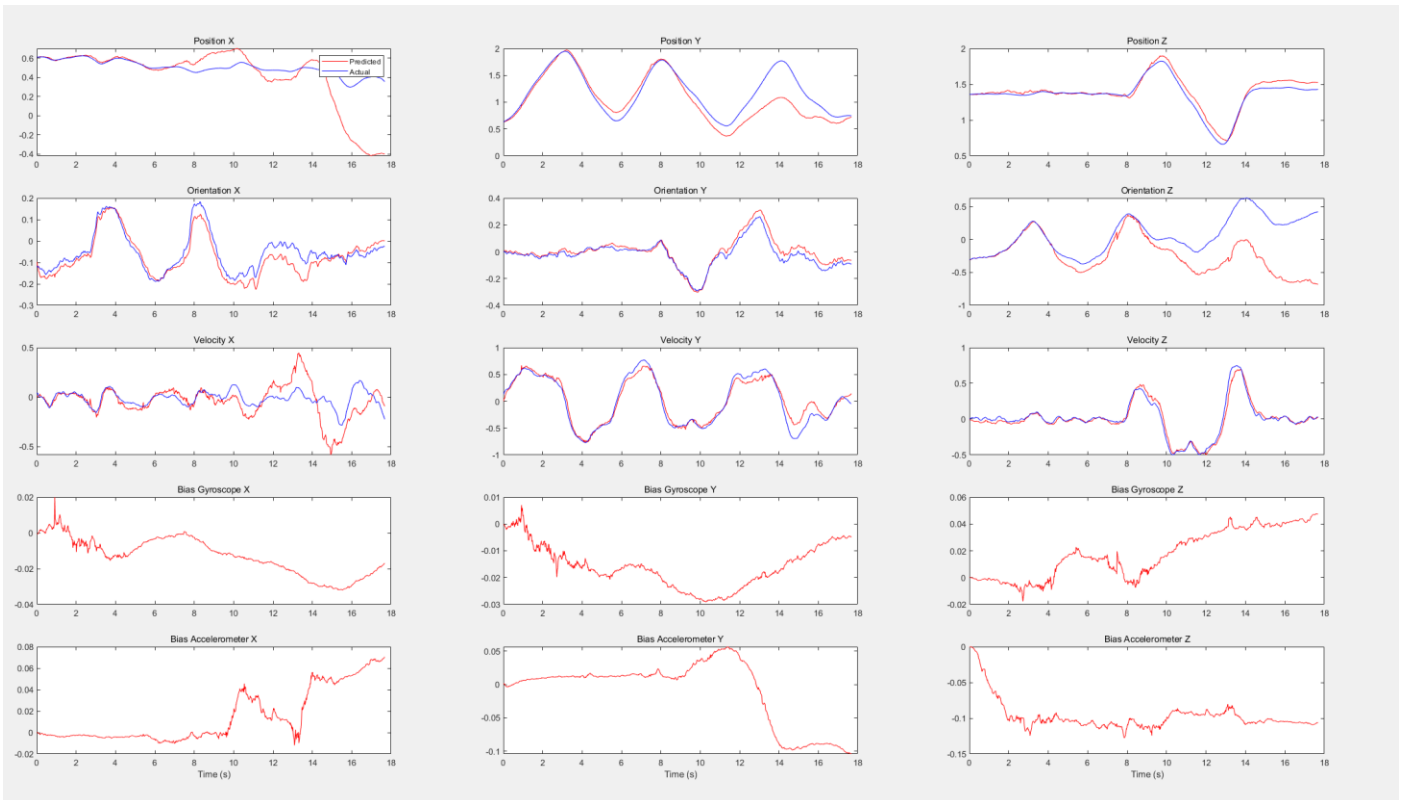
$$Z_t = g(X_{aug}, \mu_{aug})$$

$$z_{\mu,t} = \sum_{i=0}^{2n''} W_i^{(m)''} Z_t^{(i)} \quad \leftarrow \text{Update}$$
$$C_t = \sum_{i=0}^{2n''} W_i^{(c)''} \left( \chi_{aug,t}^{(i),x} - \bar{\mu}_t \right) \left( Z_t^{(i)} - z_{\mu,t} \right)^T \quad S_t = \sum_{i=0}^{2n''} W_i^{(c)''} \left( Z_t^{(i)} - z_{\mu,t} \right) \left( Z_t^{(i)} - z_{\mu,t} \right)^T$$

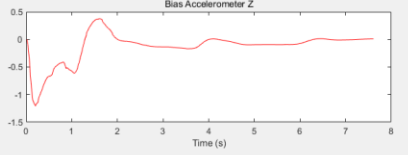
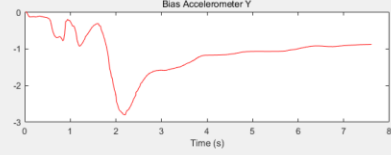
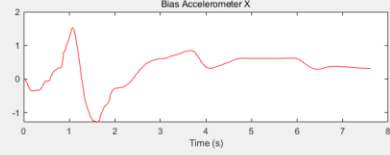
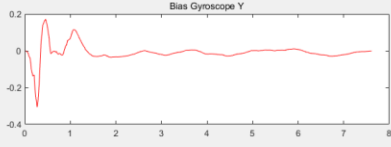
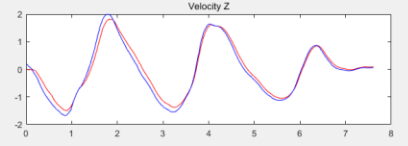
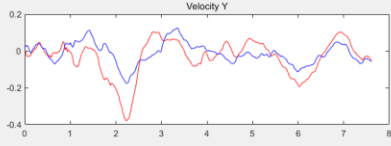
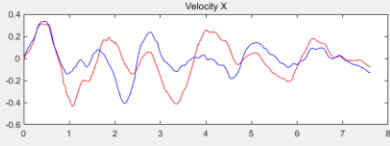
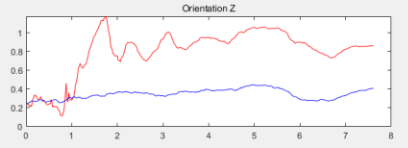
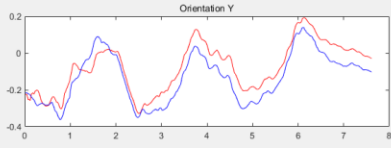
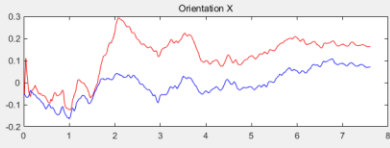
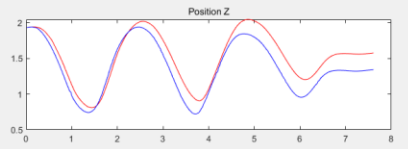
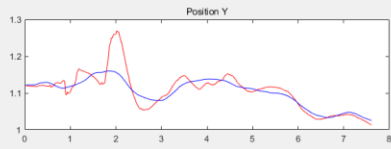
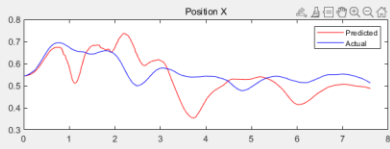
- $\mu_t = \bar{\mu}_t + K_t (z_t - z_{\mu,t})$
- $\Sigma_t = \bar{\Sigma}_t - K_t S_t K_t^T$
- $K_t = C_t S_t^{-1}$

## Plotting results:

### Datasheet 1:



### Datasheet 4:



## Conclusion

There are still some mistakes in part2-update step. I think it is due to some mistakes happened in the measurement model.