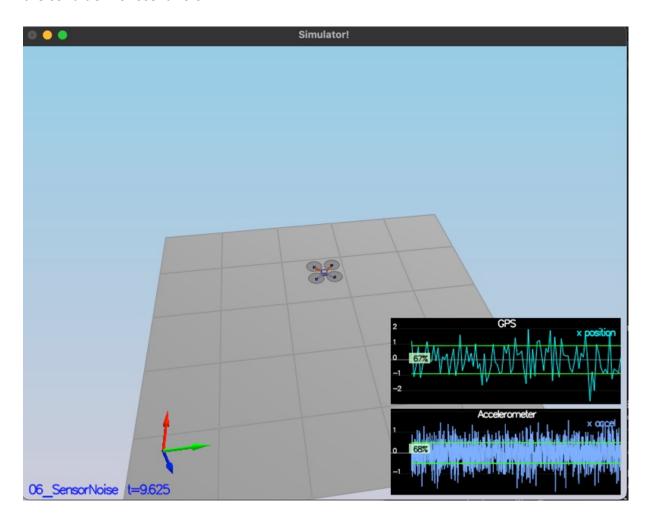
Estimation Project Write-up

06_NoisySensors

For this scenario MeaseuredStdDev_GPSPosXY and MeasuredStdDev_AccelXY were calculated based on the standard deviation from Graph1 and Graph2 data. My original estimation came as MeaseuredStdDev_GPSPosXY = 0.8 and MeasuredStdDev_AccelXY = 0.3 and I had to tune them to MeaseuredStdDev_GPSPosXY = 0.9 and MeasuredStdDev_AccelXY = 0.5, in order to satisfy the condition for scenario 6.



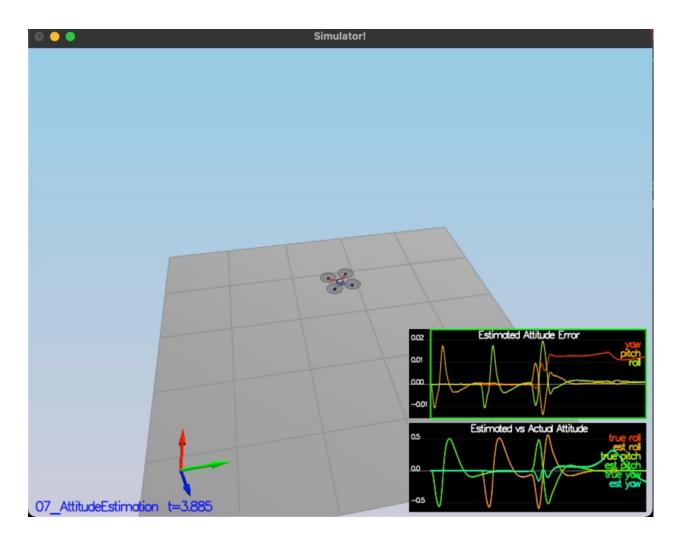
07_AttitudeEstimation

To implement better rate gyro attitude integration, the Euler's equation is used:

$$\begin{pmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{pmatrix} = \begin{pmatrix} 1 & \sin \phi \tan \theta & \cos \phi \tan \theta \\ 0 & \cos \phi & -\sin \phi \\ 0 & \sin \phi \sec \theta & \cos \phi \sec \theta \end{pmatrix} \times \begin{pmatrix} p \\ q \\ r \end{pmatrix}$$

Rotational Metrix is defined by R and Euler_dot vector is calculated based on the equation above. Finally predicted values for pitch, roll and yaw was calculated using the euler dot values

```
// SMALL ANGLE GYRO INTEGRATION:
// make sure you comment it out when you add your own code -- otherwise e.g. you might integrate yaw twice
float p = pitchEst;
float r = rollEst;
Mat3x3F R;
R(0,0) = 1;
R(1,0) = 0;
R(2,0) = 0;
R(0,1) = \sin(r) * \tan(p);
R(1,1) = cos(r);
R(2,1) = \sin(r) / \cos(p);
R(0,2) = cos(r) * tan(p);
R(1,2) = -\sin(r);
R(2,2) = \cos(r) / \cos(p);
V3F euler_dot = R * gyro;
float predictedPitch = pitchEst + euler_dot.y * dtIMU;
float predictedRoll = rollEst + euler_dot.x * dtIMU;
ekfState(6) = ekfState(6) + euler_dot.z * dtIMU;
if (ekfState(6) > F_PI) ekfState(6) -= 2.f*F_PI;
if (ekfState(6) < -F_PI) ekfState(6) += 2.f*F_PI;</pre>
```



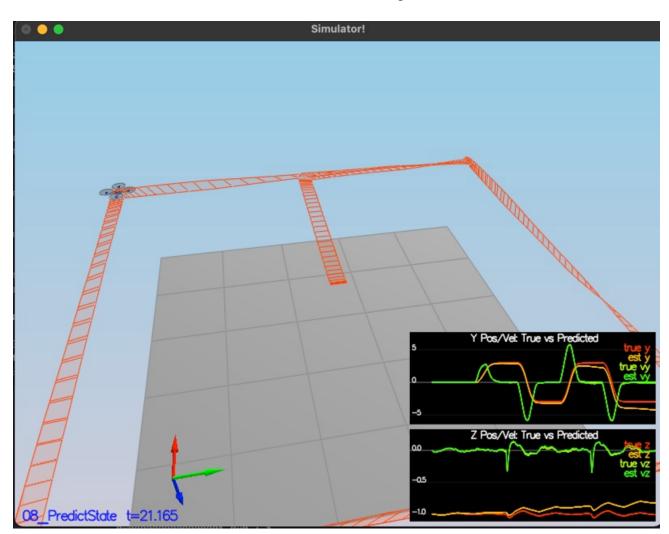
The estimated error for each of Euler angles was within 0.1 rad, for at least 3 seconds.

08_PredictState

In order to update predictedState vector, first acceleration was transformed into inertial frame by using rotation Metrix and adding gravitational acceleration. As directed, since the time duration for this prediction is shot a simplified integration method is used:

$$X_2 = X_1 + \dot{X} \cdot \Delta t$$

As a results estimated state follows the actual state with slight drift.



09_PredictionCov

To work with realistic IMU, we start by implementing RbgPrime Metrix using the equation below:

$$R'_{bg} = \begin{bmatrix} -\cos\theta\sin\psi & -\sin\phi\sin\theta\sin\psi - \cos\phi\cos\psi & -\cos\phi\sin\theta\sin\psi + \sin\phi\cos\psi \\ \cos\theta\cos\psi & \sin\phi\sin\theta\cos\psi - \cos\phi\sin\psi & \cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi \\ 0 & 0 & 0 \end{bmatrix}$$
(52)

Later we use RbgPrime in Predict function to build in Jacobian of transition function as follow:

$$g'(x_{t}, u_{t}, \Delta t) = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & \frac{\partial}{\partial x_{t}, \psi} \left(x_{t, \dot{x}} + R_{bg}[0:]u_{t}[0:3]\Delta t \right) \\ 0 & 0 & 0 & 0 & 1 & 0 & \frac{\partial}{\partial x_{t}, \psi} \left(x_{t, \dot{y}} + R_{bg}[1:]u_{t}[0:3]\Delta t \right) \\ 0 & 0 & 0 & 0 & 0 & 1 & \frac{\partial}{\partial x_{t}, \psi} \left(x_{t, \dot{z}} + R_{bg}[2:]u_{t}[0:3]\Delta t \right) \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & R'_{bg}[0:]u_{t}[0:3]\Delta t \\ 0 & 0 & 0 & 0 & 0 & 1 & R'_{bg}[1:]u_{t}[0:3]\Delta t \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & R'_{bg}[2:]u_{t}[0:3]\Delta t \end{bmatrix}$$

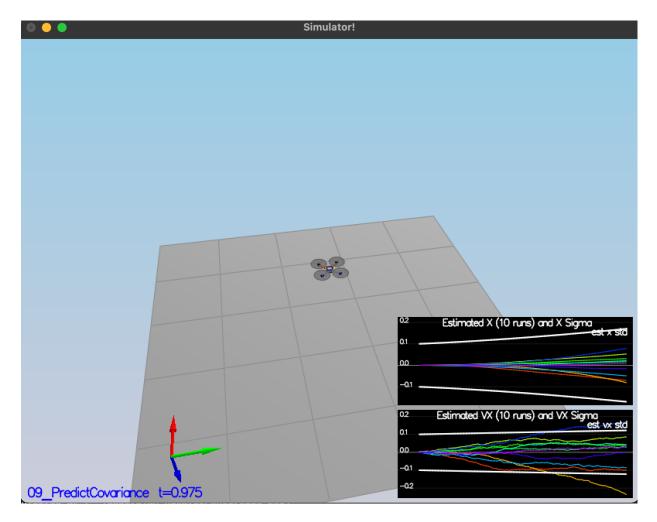
$$(50)$$

And calculating new covariance:

$$G_t = g'(u_t, x_t, \Delta t)$$

$$\bar{\Sigma}_t = G_t \Sigma_{t-1} G_t^T + Q_t$$

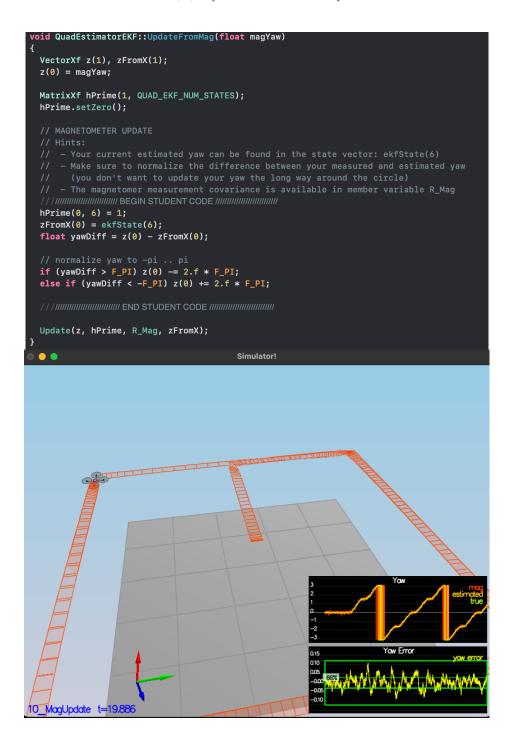
After tunning QPosXYStd and QVelXYStd process parameters, the magnitude of the error is captured as below:



10_MagUpdate

UpdateFromMag function is written based on the measurement model below:

$$h(x_t) = \left[\begin{array}{cccccc} x_{t,\psi} \end{array}
ight]$$
 $h'(x_t) = \left[\begin{array}{ccccccc} 0 & 0 & 0 & 0 & 0 & 1 \end{array}
ight]$



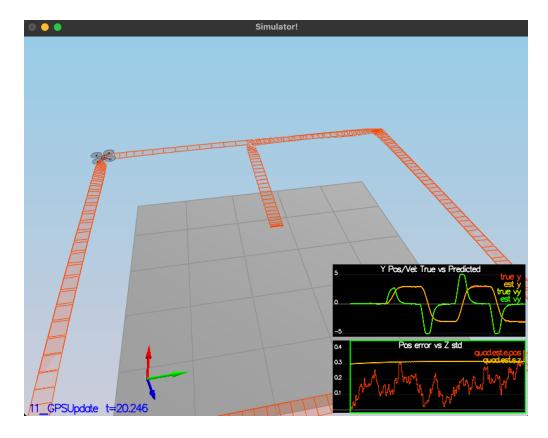
11_GPSUpdate

UpadteFromGPS function is written based on the measurement model below:

$$h(x_t) = egin{bmatrix} x_{t,x} \ x_{t,y} \ x_{t,z} \ x_{t,\dot{x}} \ x_{t,\dot{y}} \ x_{t,\dot{z}} \end{bmatrix}$$
 $h'(x_t) = egin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \ 0 & 1 & 0 & 0 & 0 & 0 & 0 \ 0 & 1 & 0 & 0 & 0 & 0 & 0 \ 0 & 0 & 1 & 0 & 0 & 0 & 0 \ 0 & 0 & 0 & 1 & 0 & 0 & 0 \ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \ \end{pmatrix}$

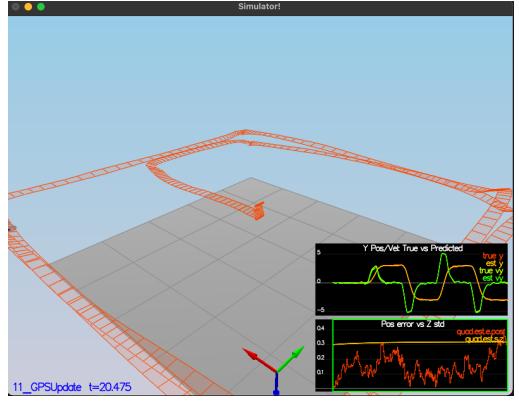
```
void QuadEstimatorEKF::UpdateFromGPS(V3F pos, V3F vel)
 VectorXf z(6), zFromX(6);
 z(0) = pos.x;
 z(1) = pos.y;
 z(2) = pos.z;
 z(3) = vel.x;
 z(4) = vel.y;
 z(5) = vel.z;
 MatrixXf hPrime(6, QUAD_EKF_NUM_STATES);
 //hPrime.setZero();
 // GPS UPDATE
 // - The GPS measurement covariance is available in member variable R_GPS
 // - this is a very simple update
 hPrime.setIdentity();
 zFromX(0) = ekfState(0);
 zFromX(1) = ekfState(1);
 zFromX(2) = ekfState(2);
 zFromX(3) = ekfState(3);
 zFromX(4) = ekfState(4);
 zFromX(5) = ekfState(5);
 Update(z, hPrime, R_GPS, zFromX);
```

Results in prediction as shown below for ideal GPS:



After tunning process noise model, the result for ideal GPS is as follow:

Simulator!



Adding the controller design from previous project:

