Exercises, module 1 week 37

UAV attitude estimation

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3 UAV attitude exercises

3.1 UAV attitude sensors

An accelerometer measures the acceleration along an axes. When the accelerometer lies static on a surface and measures the acceleration upwards, the accelerometer outputs the gravitational acceleration.

The gyro measures the angular velocity about an axes. Thus, by integrating the velocity, one has the angular position relative to an initial reference.

The magnetometer is able to measure the Earth's magnetic field and works similarly to a compass.

In an Inertial Measurement Unit (IMU), three of each sensor are used in order to measure the acceleration, angular velocity and magnetic field in 3-dimensional space which can be used to calculate a system's attitude.

3.2 UAV attitude sensing using accelerometers

3.2.1 Calculate pitch angle

In the data set used for this exercise the drone was tilted approximately $45°$ forwards and back. Equation 1 was used to calculate the pitch angle of the drone.

$$\tan \phi_{yxz} = \frac{G_{py}}{\sqrt{G_{px}^2 + G_{pz}^2}} \tag{1}$$

Figure 1 shows a plot of the calculated pitch it can be seen from the graph that the IMU is tilted $55°$ back and forth.

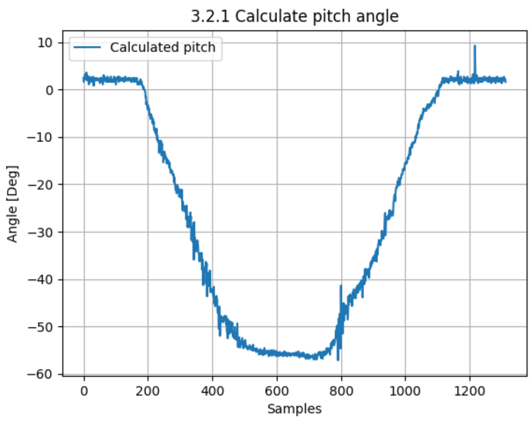

Figure 1: Pitch based on accelerometer samples.

3.2.2 Calculate roll angle

The following equation 2 is used to calculate the roll of the IMU:

$$\tan \theta_{yxz} = \frac{-G_{px}}{G_{pz}} \Rightarrow \theta = \tanh \frac{-G_{px}}{G_{pz}} \tag{2}$$

On figure 3 one can see how the roll angle moves from the initial position $-65°$ back and forth. It is also clear that noise affect the measurements.

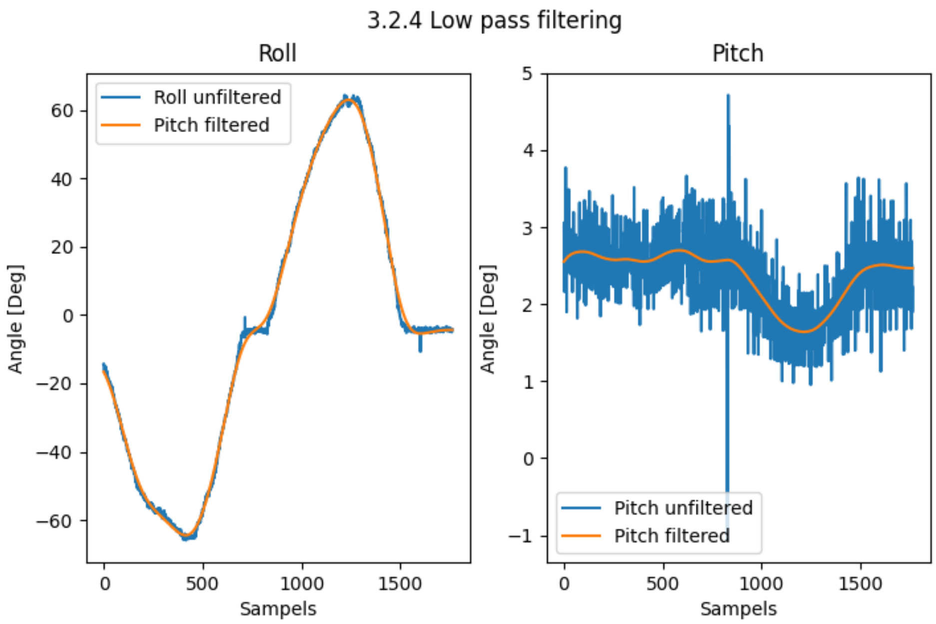

Figure 3: Roll and Pitch before and after Butterworth Lowpass filter.

3.2.3 Accelerometer noise

The data set `imu_razor_data_static.txt` was used to determine if there is noise affecting the accelerometer. Figure 2 shows the calculated pitch and roll angles from the dataset, it can be seen that there is quite a lot of noise affecting the accelerometer.

The noise source could be vibrations from the drone or the medium that the IMU is attached to.

The noise could be mitigated by using a low-pass filter, using a Kalman filter or by using a better sensor that is not as affected by noise.

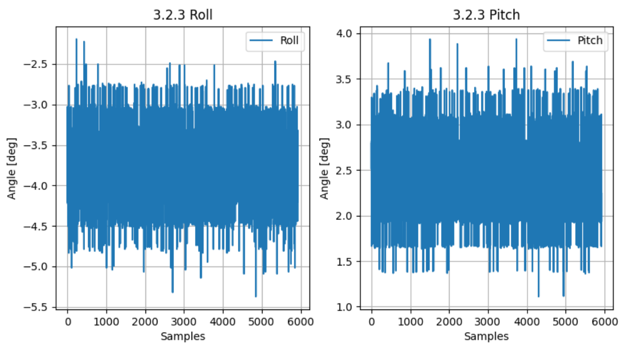

Figure 2: Noise in accelerometers.

3.2.4 Low-pass filtering

The data set `imu_razor_data_pitch_65deg.txt` was used for this exercise, and a 5th order Butterworth low-pass filter was used with cut-off at $1[Hz]$. A delay of $0.5[s]$ is added and figure 3 shows the filtered and unfiltered data.

However with this much delay in the system it is not acceptable for use in a UAV attitude controller which needs to react swiftly in order to avoid crashing.

3.2.5 Limitations of Euler angles

The limitations of Euler angels is that gimbal lock can occur. Gimbal lock occurs when two out of three gimbals are in the same plane resulting in loss of a degree of freedom.

The problem can be circumvented by using quaternions.

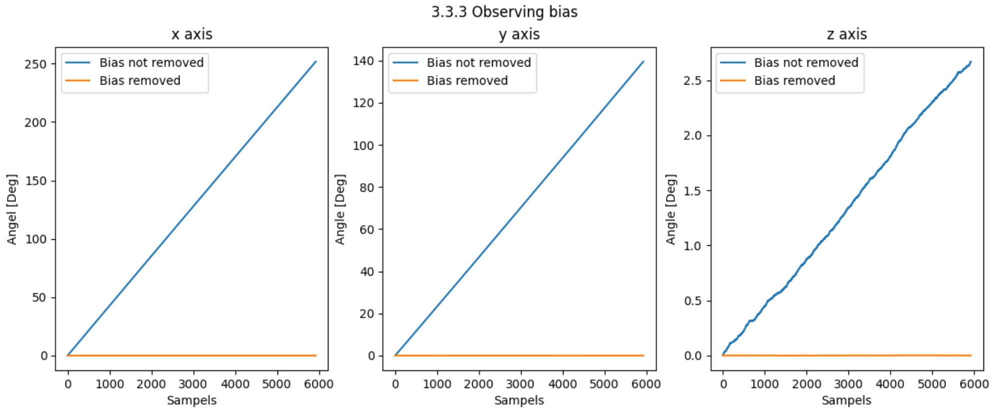

Figure 5: Angular position drift from gyro sample integration.

3.3 Gyro measurements

3.3.1 Calculating relative angle

The data set `imu_razor_data_yaw_90deg.txt` was used to calculate the relative angle based on the gyro reading by numerical integration of the gyros outputted angular velocities. The resulting angular position can be seen in figure 4

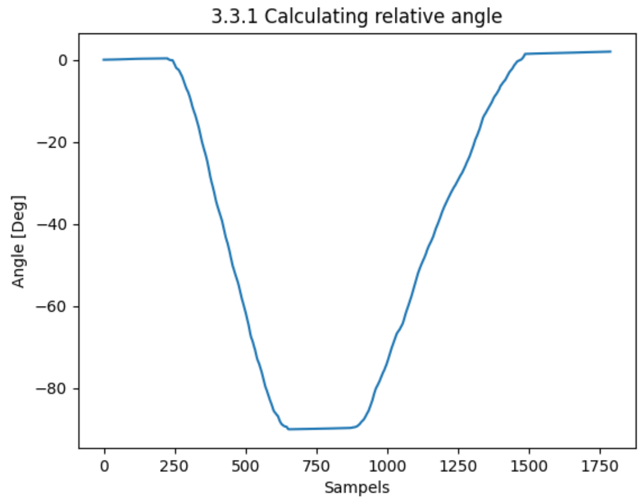

Figure 4: Yaw from gyro samples.

3.3.2 Static data

By integrating the sampled data on a static surface, the blue line in figure 5 shows the calculated relative angular positions.

Since the IMU is held static, the expected result is a horizontal line, but the bias accumulates through the numerical integration, simulating a constant drift in position.

3.3.3 Observing bias

The gyro bias is estimated by finding the slope of the line with $\frac{y_2-y_1}{x_2-x_1}$. The estimated biases can be seen in table 3.3.3. The gyroscope variance is calculated based on all three gyros as $0.931 10^{-3} \left[\frac{rad^2}{s^2}\right]$.

Axis	Estimated bias $\left[\frac{rad}{s}\right]$
x	0.0007417244191025366
y	0.0004109444493122052
z	7.866362791301079e-06

Figure 4, shows the bias on all three axis. The blue line indicates the raw data and the orange line represents the data with the bias removed.

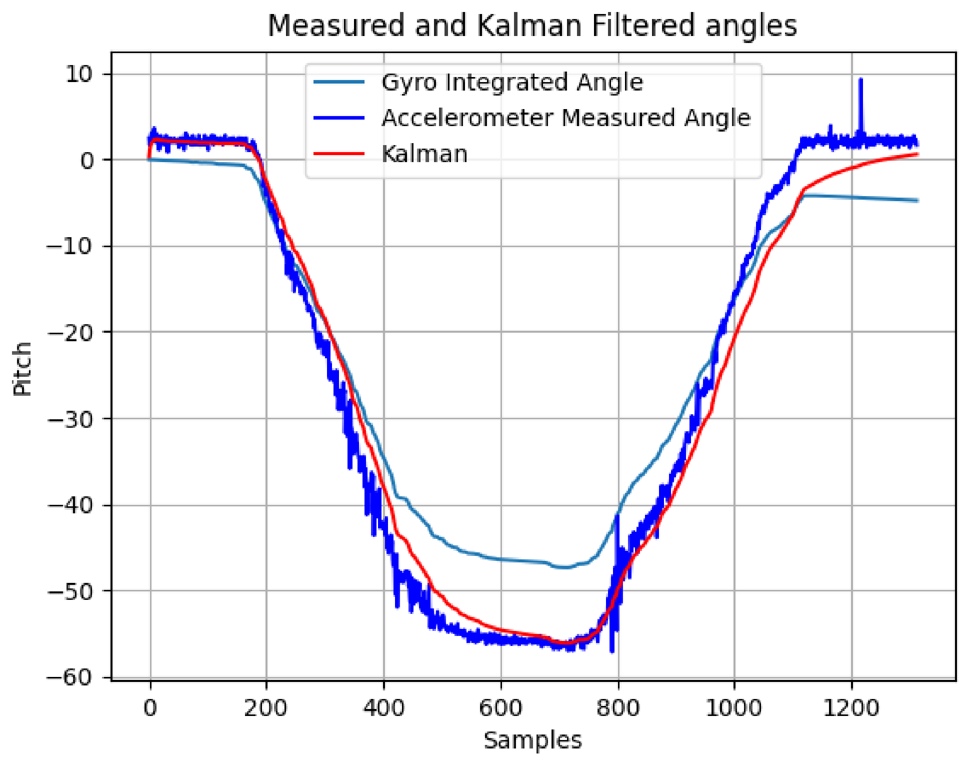

Figure 6: Raw accelerometer samples and Kalman filtered version.

3.3.4 Bias sources

The noise in the gyroscope is likely to be cause by random vibrations and magnetic fields from surrounding sources or from within the IMU itself.

3.4 Kalman filter

3.4.1 Implementing a scalar Kalman filter

The Kalman prediction and correction pseudo-code from the given *kalman_filter_notes.pdf* are used to implement these steps in the `imu_exercise_kalman.py`-file.

The calculation of pitch is similar to that in equation 1 and the pitch variance is calculated to be $0.149\ \left[rad^2\right]$.

The gyro sensor data along x is used in the prediction step. The pitch is calculated with the less noisy accelerometer data and is used in the correction step.

The values are instantiated with the means and variances of the data from `imu_razor_data_static.txt` and the accelerometer variance and estimated initial pitch and variance are instantiated by trial and error guesses to $0.1\left[\frac{m^2}{s^4}\right]$, $\frac{-\pi}{4}\ [rad]$ and $\pi\ \left[rad^2\right]$, respectively.

The pre- and post-filter pitch are finally plotted in figure 6 next to the sampled accelerometer data.

It can clearly be seen how the Kalman filter removes the noise and yields a more stable pitch.