

## Journal 1

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## 1 UAV attitude exercises

### 1.1 UAV attitude sensor

A MEMs accelerometer measures the displacement of a small proof mass. The displacement is measured by a change in capacitance between the mass and sensing plates inside. The accelerometer measures the difference between any linear acceleration in the accelerometers reference frame and the earth's gravitational field vector. In the absence of any acceleration the accelerometer measures the rotated gravitational field vector which can be used to determine the accelerometers pitch and roll angles.

The working principle of the MEMs gyroscope is built upon the vibrating structure gyroscope. The underlying physical principle is that a vibrating object tends to continue vibrating in the same plane even if its support rotates. This exerts a force on the supports that can be measured and translated into the rate of rotation.

A Magnetometer measures the direction and strength of the earth's magnetic field vector.

### 1.2 UAV attitude sensing using accelerometers

#### 1.2.1 Calculate pitch angle

Observing figure 1 below, it's clear that the IMU has been tilted 55° to one side and then back again to horizontal.

The angle has been calculated using eq. 1. It is clear, that going only by accelerometer, the system is sensitive to noise spikes. The worst "offense" is where it changes almost 10°, but it should have been stable.

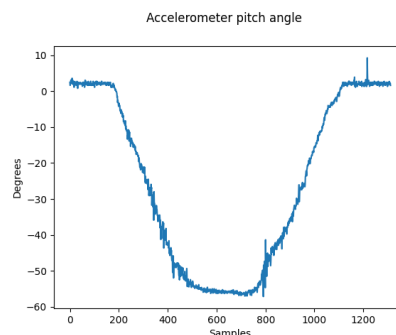


Figure 1: The calculated pitch angle

$$\phi = \text{atan2}(\text{acc}_y, \text{acc}_x^2 + \text{acc}_z^2) \quad (1)$$

#### 1.2.2 Calculate roll angle

Calculation of the accelerometer roll angle is carried out by using equation 2. The result is shown in figure 2.

$$\theta = \text{atan2}(-\text{acc}_x, \text{acc}_z) \quad (2)$$

From the graph it is clear that the calculated angle follows the expected value, 65°. Besides this, the graph shows clear indications of random noise and a couple of noise spikes.

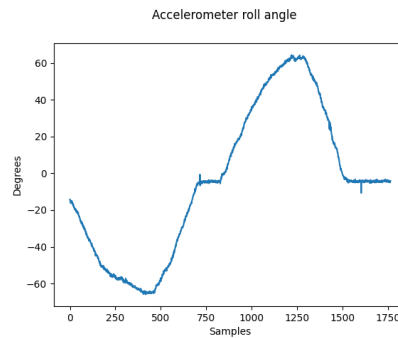
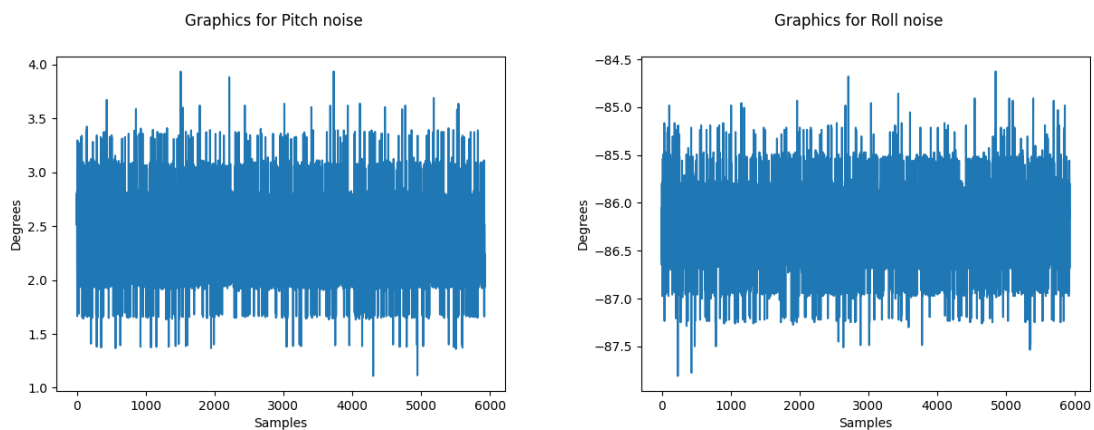


Figure 2: The calculated roll angle



(a) This subfigure shows the offset from 0 on the pitch angle due to bias  
 (b) This subfigure shows the offset from -90 on the roll angle due to bias

Figure 3: Shows the accelerometer noise for both pitch and roll

### 1.2.3 Accelerometer noise

Observing figure 3, it is clear that there is both noise and bias. The bias is seen as a  $+2.5^\circ$  offset of the pitch angle, and a  $5^\circ$  offset of the roll angle.

The bias could be mitigated by calibrating the drone and subtracting the bias - if known. The noise can be smoothed using a filter - lowPass, Kalman etc.

### 1.2.4 Low-pass filtering

In this section two lowpass filters has been implemented and tested in an attempt to minimize noise. The first one is a simple 1st order averaging filter, implemented with equation  $(y_{nT} = x_{nT} + x_{(n-1)T})$ , see fig 4a.

The second is a 4th order Butterworth filter, implemented using the python lib *SciencePy*, see figure 4b.

It is crucial that the noise is smoothed to ensure a steady and level flight, as is elimination of noise spikes that could cause the drone to jump.

Observing the graphs, it is clear that both filters attenuate some of the noise. The averaging filter reduces the noise spike around 700 samples, but random noise is still present. The Butterworth filter almost removes the noise and noise spikes. This is expected since the filter attenuated the signal with 24dB/oct, where the averaging filter only attenuates with 6dB/oct.

One important thing to notice is the phase-lag. Where the averaging filter introduces no phase-lag, see its equation, the Butterworth filter produces a, roughly estimated, 30 sample phase-lag yielding almost 30mS delay. The issue with signal delay is that the drone will be slower to respond which, for the pilot, will make the controls feel sluggish.

### 1.2.5 Limitations of Euler angles

The issue with Euler coordinates is that there are certain configurations where you run into a gimbal lock. A gimbal lock is when one or more axes are aligned and we therefore lose one or more DOF. One of the

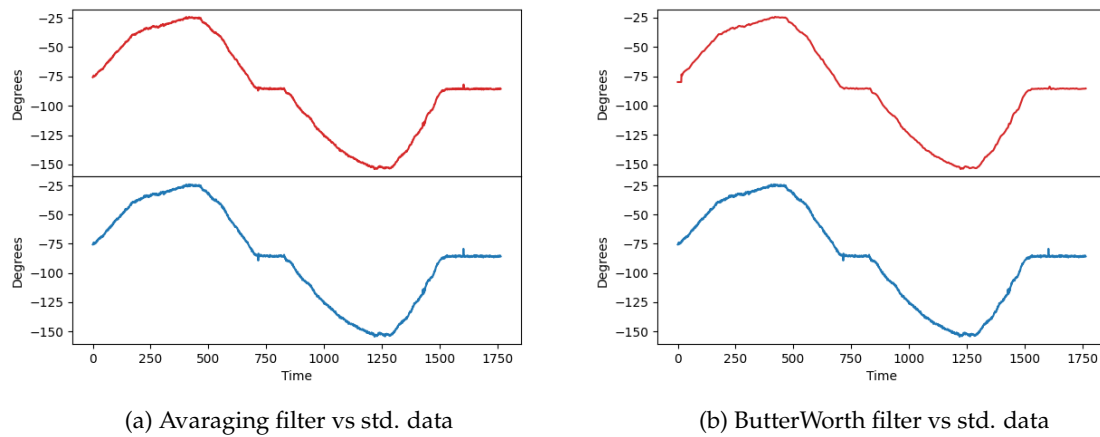


Figure 4: Lowpass filters

orientations that causes a gimbal lock is when the drone pitches up  $90^\circ$  as the yaw and roll rings becomes parallel, which causes that changes in the yaw and roll to have the same effect on the drone/not being able to compensate for each other.

This can be mitigated by adding a fourth dimension - or a fourth rotational axis. It has the drawback that it always needs to be  $90^\circ$  out of alignment of the innermost rotational axis.

### 1.3 Gyro measurements

#### 1.3.1 Calculating relative angle

The gyroscopes relative angle has been calculated by simple numerical integration which is given by the formula:

$$y_n = \sum_{i=0}^n (x_i + \Delta T) \quad (3)$$

$y_n$  is the relative angle,  $x_n$  is the raw data and  $\Delta T$  is the time difference between 2 consecutive samples.

The graph in figure 5 plots the relative angle per sample. The graph shows an almost  $90^\circ$  turn with no noise.

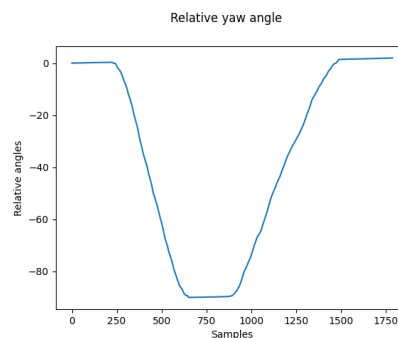


Figure 5: Gyroscope relative angle

The issue with integration is that it steadily adds any noise spikes to the resulting angle giving a smooth graph but constantly increases the bias.

#### 1.3.2 Static data

As a continuum to the statement above, a numerical integration is performed on static data. The static data is sampled with the gyroscope placed on a horizontal, flat surface. The graph shows a steadily increasing drift which further the suspicion that the integration increases the bias.

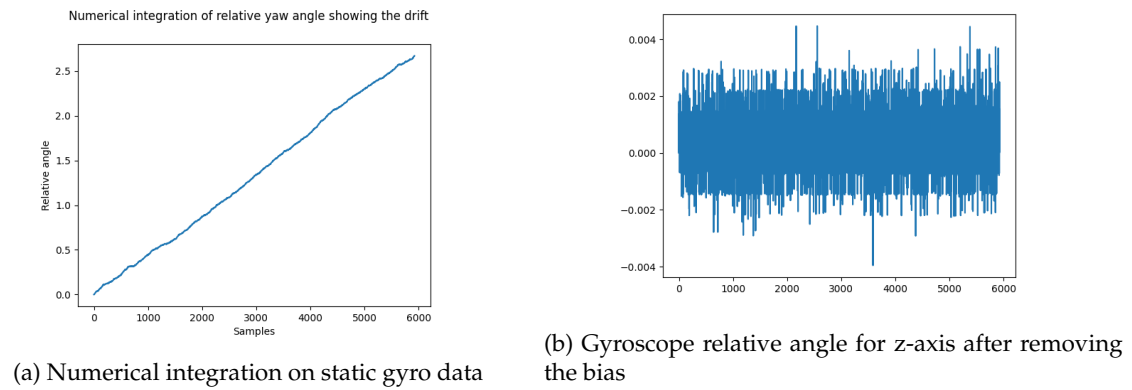


Figure 6: Graphical view of the increasing bias [left] and the statis data with the increasing bias removed [right]

### 1.3.3 Observing bias

The graph in figure 6b plots the relative angle of the static gyroscope data with a bias estimate, in form of a rolling variance, subtracted before integration.

The graph shows almost no noise, and the bias has been corrected to a fraction of a degree. Notice that the variance is a postive only value, which explains the tiny positive bias.

### 1.3.4 Bias sources

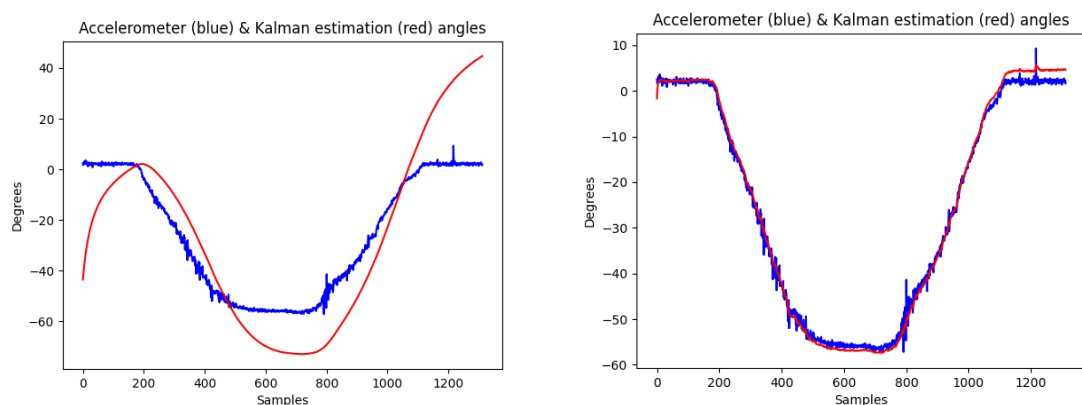
A biased signal is a signal subjected to systematic variation. A potential source of bias is an unlevel surface when calibrating, as the the gyro will inherit any offset as bias.

Noise is random variation around the signals true value. Noise is typically introduced through electrical interference. This interference might originate from the motors back EMF and the switching frequency of the ESC.

## 1.4 Kalman filter

### 1.4.1 Implementing a scalar Kalman filter

The Kalman filter has been implemented with the supplied pseudo code. For correct performance the filter is supplied with start guesses for the variance and angle parameters. A wrong guess results in a filter that won't converge as shown in figure 7a. An optimal start guess will make the filter converge faster as shown in figure 7b.



(a) Kalman filter with bad estimates of the pitch angle (b) Kalman filter with better estimates of the pitch angle

Figure 7: Two Kalman filter estiamtes of the pitch angle