

1 Problem Description

The purpose of this report is to show how an error-state Kalman filter (ESKF) can utilize IMU and GNSS measurements to track a flying object. For this we are given two datasets. The first dataset is simulated and includes a truth value, this allows for calculation of Normalized Estimation Error Squared (NEES) values, to tune with regards to estimation error. For both datasets we can compute Normalized Innovation Squared (NIS) to tune with regards to error in the innovation.

2 ESKF

3 Tuning

3.1 Process

The initial parameters, based on the sampling time and expected noise of the sensor and the sampling time, provided a good starting point. What was lacking appeared to be an ability of the system to make proper turns. A possible explanation is that the calculated noises don't account for any significant maneuvering. The noises should therefore be slightly increased in order for the filter to also account for reasonable changes in attitude and position. NEES values for the individual gyroscope and accelerometer axes were also used for more detailed tuning. A short outline of the initial tuning process is listed here along with a discussion below.

1. Tune measurement noise until the GNSS track is followed
2. Tune process noise to get a decent result from NEESes
3. Tune IMU bias driving noises to reduce trends in gyro and acceleration NEES bias
4. Tune individual measurement and process noise parameters to fit individual IMU NEES axis in the middle of interval

An observation made was that certain large deviations occurred in the NEESes. This appears to be due to larger than normal changes in position and attitude. Due to the infrequent GNSS updates, the process noise was increased while the measurement noises were decreased to try to better account for these occurrences. The reasoning being that the IMU might be able to track the true value better. Reducing measurement noise in favour of process noise also improved NIS results, by reducing overfitting in parts of the track.

The tuning appeared in large part to be a bias-variance tradeoff problem. Our experience was that reducing the variance during fast maneuvers led to

overfitting elsewhere. Likewise acceptable bias-variance on most of the track tended to cause underfitting during fast maneuvers. From a practical point of view we would argue that it makes more sense to track the harder parts better and accept some overfitting elsewhere if the alternative is to have huge errors in certain parts of the track. There is ofcourse a tradeoff and

Results		
Parameter	Simulated data	Real data
NIS mean	1.4971	004
NEES tot mean	13.0695	248
NEES pos mean	1.4101	008
NEES vel mean	0.9584	012
NEES att mean	0.9281	016
NEES acc bias mean	5.3252	020
NEES gyro bias mean	0.9258	024
Estimated pos RMSE	0.5637	024
Estimated vel RMSE	0.3485	024
Measured pos RMSE	0.6735	024

States estimates

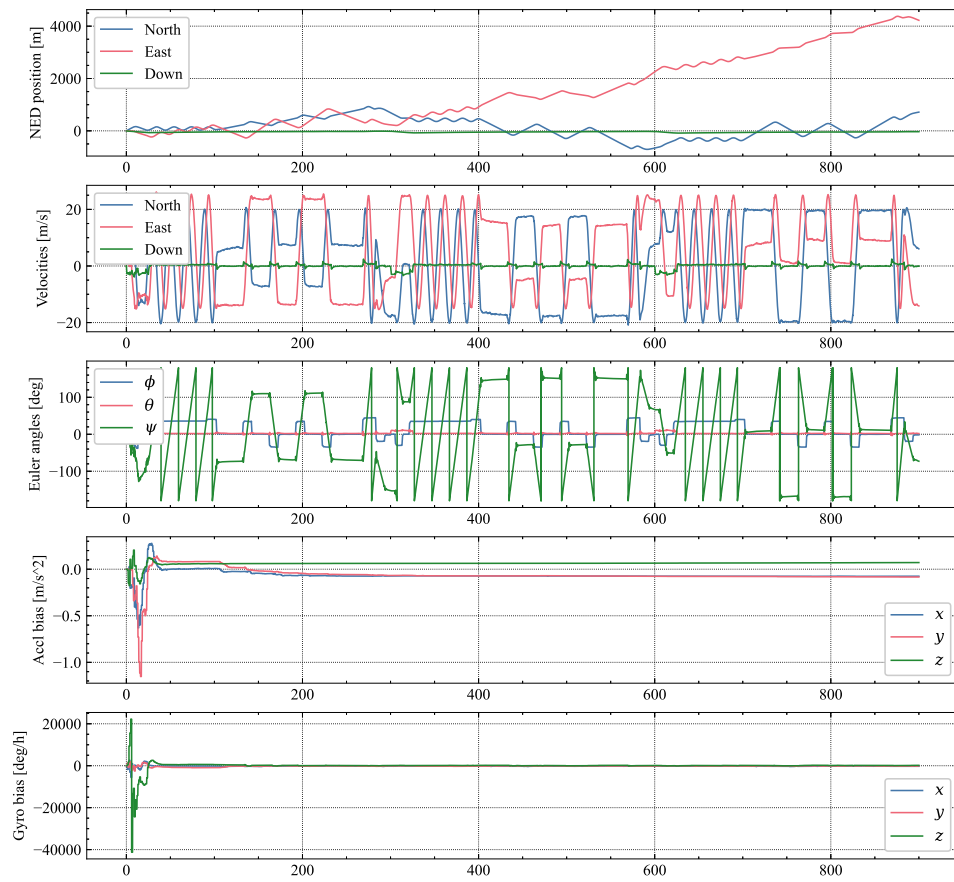


Figure 1: Estimated states

States estimate errors

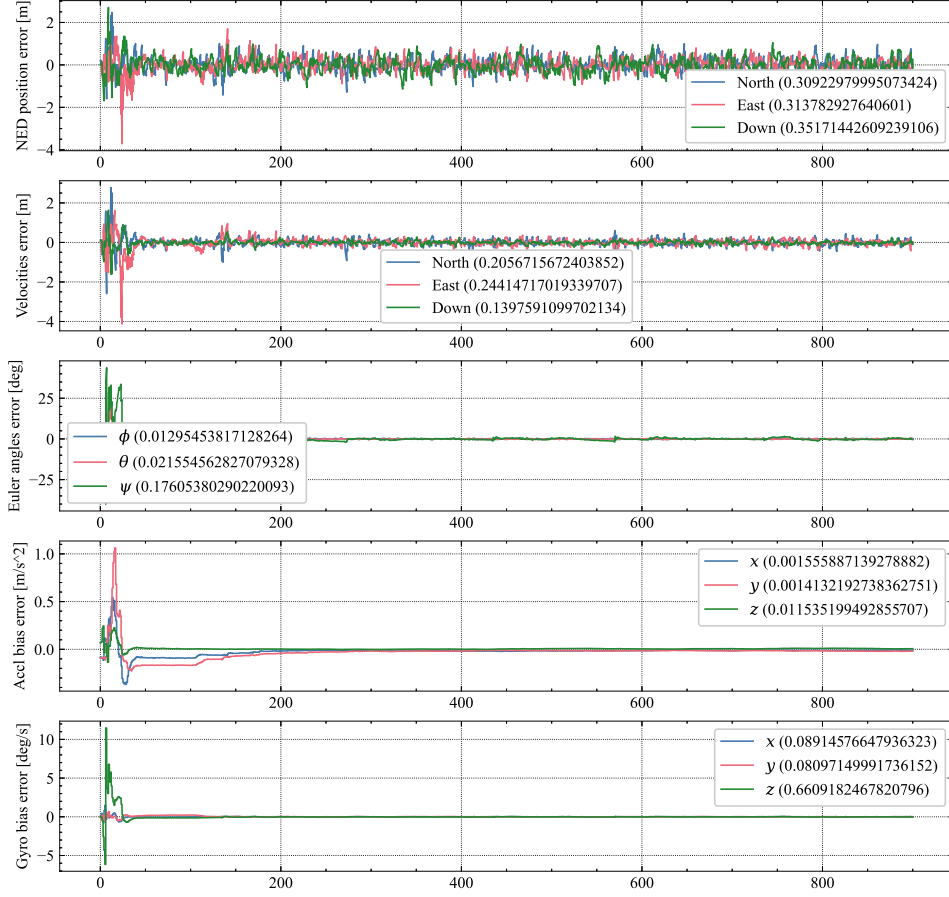


Figure 2: True error states

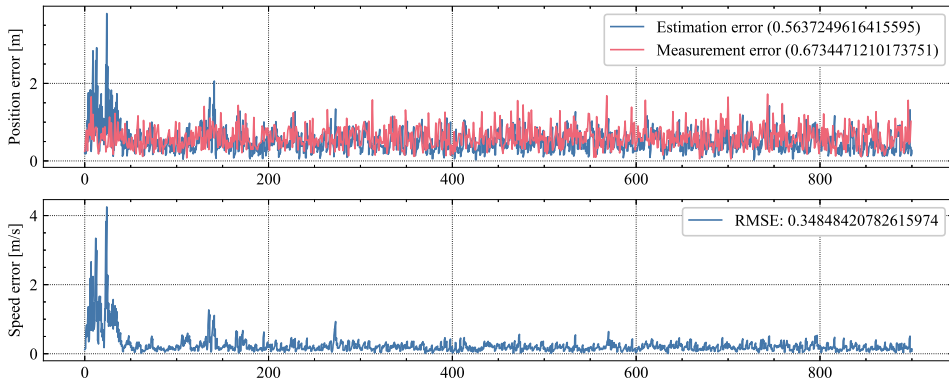


Figure 3: Error distance

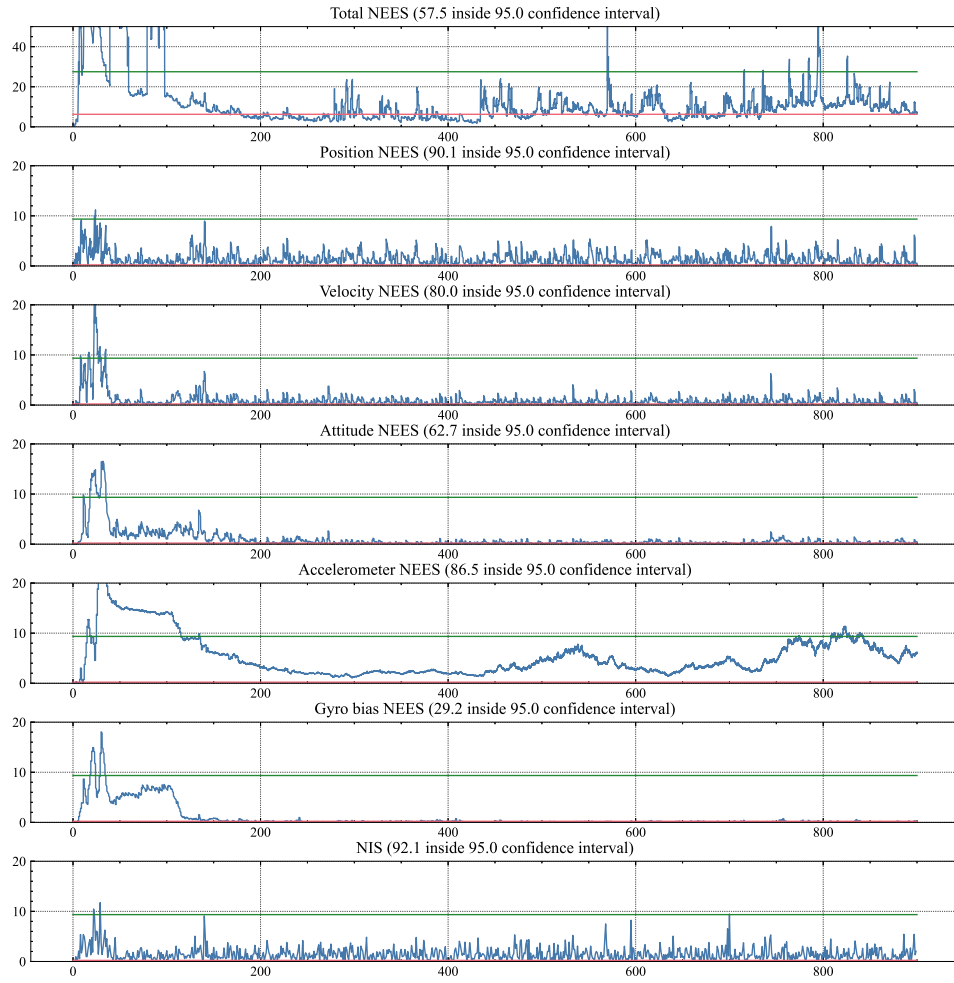


Figure 4: NEESes and NIS

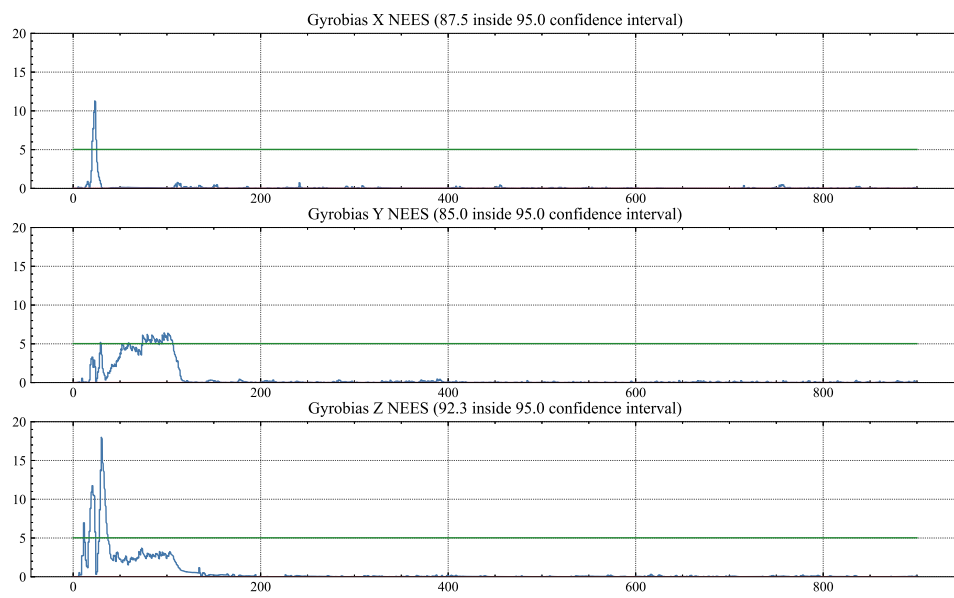


Figure 5: Assignment 2. Task 3. States