Institut für Erdmessung
- Positionierung und Navigation –
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Inertial Navigation

-Exercise 2-

Sensor Errors

Deadline: 13.12.2023

While inertial sensors provide an exceptional way to estimate the 3D kinematic state of a plattform in an autonomous manner, the measurement principle of integrating the base signals accelerations/turn rates is quite troublesome in reality. Already after a short timespan, the integrated errors of the base signals, as well as external perturbations, can lead to tremendous deviations in the navigation solution if not handled properly. The sensor errors can be classified as systematic and stochastic. This exercise will introduce methods and options to handle both error classes.
First, the deterministic biases and scale factors of an IMU have to be estimated in a „6 position test“. After that, different stochastic processes have to be characterized with the help of the Allan-deviation. Further, real instrument data has to be analyzed to estimate the white noise density and the bias instability, two characteristics often given in sensor datasheets. Finally, the connection of the Allan-variance and the power spectral density of a signal will be focused on, which is quite useful to model the process noise of the system in a Kalman filter framework.

Tasks:

Deterministic effects
Use the „ex02_task1_matr#.mat“ dataset

1. Estimate bias and scale factor of the three accelerometer and gyro-axes of your IMU. What would you expect of a perfect sensor and why may the results be different?

Stochastic effects
Use the „ex02_task2_matr#.mat“ dataset, which includes 4 timeseries of 1 [Hz] stochastic processes (a,b,c,d). You need to implement the Allan-deviation algorithm in order to proceed.

2. a) Plot the original timeseries, as well as the respective temporal differentiation in first and second order (Matlab: diff())
   Name 2 effects that the differentiation has on the data.
   b) Compute the Allan-deviation for all processes and display them in a common loglog-plot.
   c) Estimate the sum-process (a+b+c+d) and add it to the plot. Outline the area in which each single process dominates (also mark the underlying stochastic processes in the same way).
   Why is the classic standard deviation not enough to characterize those processes?

IMU long-term stability
Use the „ex02_task3_matr#.mat“ dataset

3. a) Plot the raw data of your IMU over time. What noise processes do you expect by the look on the graph?
   b) Estimate the Allan-deviation of all sensor axes (accelerometer & gyro) from the static dataset (frequency data). Plot the results.
   c) Read each axis' bias instability as well as the white noise density from the plot. Compare them with the manufacturer datasheets (see StudIP). Discuss the results!

Power spectral density

4. The analyzation of sensor data can alternatively be done in frequency domain.
   a) Calculate the analytical power spectral density of all different processes you identified in task 3 for the acceleration and turn rate-data on the **z-axis**. Use the h-α coefficients from the Allan-Plots
   b) The PSD can as well be gained directly from the raw sensor data by a fast Fourier transformation (FFT). Use the StudIP function „aux_calcPSD“ to estimate the PSD directly from the measurement of the z-Axis.
   Compare the results from 4a and 4b in a common plot. What may be the advantages of the different representation in time/frequency domain?

Please send your results (report, .csv and code) to:

weddig@ife.uni-hannover.de

Email subject:	Report_inav_ex02
Report name:	ex02_surname_name_matrikel.pdf
Results file:	ex02_matrikel.csv
Code:	ex02_matrikel.zip