Inertial sensors are essential elements in many modern flight control systems, navigation systems, and data logging devices. Modern inertial sensors are highly accurate and robust, but they are still physical measuring devices with product imperfections. Inertial sensors functionality are influenced by environmental factors, such as temperature and magnetic field. Biases due to imperfections and environmental factors, if left uncorrected, would result in erroneous navigational states, incorrect aerodynamic models, and potential failures of the flight control system.

Modern inertial sensors are highly accurate and robust, but they are physical measuring devices with product imperfections. Inertial sensors functionality are influenced by environmental factors, such as temperature and magnetic field. Biases due to imperfections and environmental factors, if left uncorrected, would result in erroneous navigational states, incorrect aerodynamic models, and potential failures of the flight control system.

The objective of this PhD project is to develop a general calibration procedure for inertial sensors, that eventually be implemented on the Autronic AC2266L 2-axis calibration table.

**Background and Objective**

The objective of this PhD project is to develop a general calibration procedure for inertial sensors, that eventually be implemented on the Autronic AC2266L 2-axis calibration table.

**Research Progress**

Most of the studies in the first year were related to the measurement set up and experiments to determine the proper input sequence using a fiber optic gyroscope. The two separate calibration table (CT) and sensor data acquisition systems issue were solved using two additional connection in the measurement system. The second is a clock connections for coordinating the sampling in control cabinet and DAS PC. The different sampling frequency was the biggest issue; aligning both data in the post processing had been a good solution.

A preliminary calibration procedure for a new type of sensor, angular accelerometer (AA), was started in the second year. The CT is a position table, which means it only measure angular displacement, subsequently estimate the angular rate and angular acceleration. It provides accurate rate data but not acceleration. Therefore, improving angular acceleration data is important to have a good reference to calibrate AA. Sliding mode differentiator is used to obtain angular acceleration from position data. The new reference still have some oscillation at the peak of the sine that is subject to further investigation. Considering only the angular acceleration data to do the calibration, the 1-D polynomial model 3rd order is the best fit.

**Model structures**

1-D, 2-D and 2-D coupled polynomial

- \[ f(x) = \sum_{i=0}^{n} a_i x^i = a_0 + a_1 x + \ldots + a_n x^n \]
- \[ f(x, y) = \sum_{i=0}^{n} \sum_{j=0}^{m} c_{ij} x^i y^j \]
- \[ f(x, y) = c_{00} + c_{01} x + \ldots + c_{0n} x^n + \ldots + c_{m0} y + \ldots + c_{mn} y^n \]

\( x \) is measured sensor data; \( y \) is measured or derived sensor data; \( a_i, b_i, c \) are polynomial parameters

**Model Evaluation**

- Residual Root Mean Square
  \[ \text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |\epsilon_i|^2} \]
  \( N \) is the number of data points; \( \epsilon \) is the residual
- Akaike Information Criterion
  \[ AIC = 2k - 2\log(L) \]
  \( k \) is the model’s number of parameter; \( L \) is the model’s maximized value of the likelihood function

**Calibration System Schematics and Method**

The CT consist of two subsystems: the control cabinet and the calibration table, while the two other subsystems are the sensor and the DAS PC.

**Calibration Procedure**

1. Measure Angular Acceleration (1-D)
2. Measure Angular Acceleration (2-D)
3. Measure Angular Acceleration (2-D coupled)
4. Use the calibration table as a reference to calibrate AA.
5. Use sliding mode differentiator to obtain angular rate and angular acceleration.
6. The two separate calibration table (CT) and sensor data acquisition systems issue were solved using two additional connections in the measurement system.
7. The second is a clock connections for coordinating the sampling in control cabinet and DAS PC.
8. The different sampling frequencies were the biggest issue; aligning both data in the post processing had been a good solution.

**Model Evaluation**

- Residual Root Mean Square
  \[ \text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |\epsilon_i|^2} \]
  \( N \) is the number of data points; \( \epsilon \) is the residual
- Akaike Information Criterion
  \[ AIC = 2k - 2\log(L) \]
  \( k \) is the model’s number of parameter; \( L \) is the model’s maximized value of the likelihood function

**Model structures**

1-D, 2-D and 2-D coupled polynomial

- \[ f(x) = \sum_{i=0}^{n} a_i x^i = a_0 + a_1 x + \ldots + a_n x^n \]
- \[ f(x, y) = \sum_{i=0}^{n} \sum_{j=0}^{m} c_{ij} x^i y^j \]
- \[ f(x, y) = c_{00} + c_{01} x + \ldots + c_{0n} x^n + \ldots + c_{m0} y + \ldots + c_{mn} y^n \]

\( x \) is measured sensor data; \( y \) is measured or derived sensor data; \( a_i, b_i, c \) are polynomial parameters

**Challenges**

- Various type of inertial sensors
- Determine input sequence
- Angular Acceleration Reference data
- Two separate data acquisition systems
- Choose function approximation
- Calibrate multi-sensor
- Simulate Temperature

**Calibration Procedure**

1. Measure Angular Acceleration (1-D)
2. Measure Angular Acceleration (2-D)
3. Measure Angular Acceleration (2-D coupled)
4. Use the calibration table as a reference to calibrate AA.
5. Use sliding mode differentiator to obtain angular rate and angular acceleration.
6. The two separate calibration table (CT) and sensor data acquisition systems issue were solved using two additional connections in the measurement system.
7. The second is a clock connections for coordinating the sampling in control cabinet and DAS PC.
8. The different sampling frequencies were the biggest issue; aligning both data in the post processing had been a good solution.

**Model Evaluation**

- Residual Root Mean Square
  \[ \text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |\epsilon_i|^2} \]
  \( N \) is the number of data points; \( \epsilon \) is the residual
- Akaike Information Criterion
  \[ AIC = 2k - 2\log(L) \]
  \( k \) is the model’s number of parameter; \( L \) is the model’s maximized value of the likelihood function

**Model structures**

1-D, 2-D and 2-D coupled polynomial

- \[ f(x) = \sum_{i=0}^{n} a_i x^i = a_0 + a_1 x + \ldots + a_n x^n \]
- \[ f(x, y) = \sum_{i=0}^{n} \sum_{j=0}^{m} c_{ij} x^i y^j \]
- \[ f(x, y) = c_{00} + c_{01} x + \ldots + c_{0n} x^n + \ldots + c_{m0} y + \ldots + c_{mn} y^n \]

\( x \) is measured sensor data; \( y \) is measured or derived sensor data; \( a_i, b_i, c \) are polynomial parameters

**Publication**