DESIGN AND IMPLEMENTATION OF SENSING AND ESTIMATION SOFTWARE IN AGGIENAV, A SMALL UAV NAVIGATION PLATFORM

Calvin Coopmans, Haiyang Chao and YangQuan Chen

Center for Self-Organizing and Intelligent Systems (CSOIS),
Electrical and Computer Engineering Department,
Utah State University, Logan, UT 84322 – 4120, USA
E-mails: {cal.coopmans, haiyang.chao}@aggiemail.usu.edu, yqchen@ieee.org

ABSTRACT

Small UAV performance is limited by the sensors and software filters used in the navigational systems. Several solutions of various complexity and cost exist, however no ready-made solutions exist for a high-accuracy, low-cost UAV system. Presented is the design (low-level system as well as high-level extended Kalman filter) for a specifically designed small-UAV navigation platform, AggieNav.

NOMENCLATURE

UAV Unmanned Aerial Vehicle.
IMU Inertial Measurement Unit. Typically a 3-axis roll rate gyro co-axial with a 3-axis accelerometer.
INS Inertial Navigation System. Suggests a combination of IMU and other sensors such as GPS via a software filter.
UAV Unmanned Aerial Vehicle.

INTRODUCTION

To accomplish mission goals or to fly passengers to their destinations, all aircraft rely on sensors for the core of their navigational systems. For small UAVs, the sensor suite determines much about the usefulness and capabilities of such a system, and is mostly limited because of the relatively high cost of high-quality navigational sensors and equipment.

The options for low-cost miniature attitude navigation sensing are few; most inexpensive, small fixed-wing UAVs use infrared thermopiles sense the relative heat differential from the black body radiation of the Earth’s surface. While this technique does work, it is not accurate enough for some remote measurement tasks and has problems when flying near large land features such as mountains and through valleys. Combined with a modern civilian GPS receiver, navigation is possible.

Inertial measurement units with roll-rates and accelerometers are the standard sensor for attitude determination in flight. Several solutions exist for navigation in small UAVs, such as, all of which use Kalman or other state-estimation filter of some kind to provide a high-accuracy estimation of the current position and attitude of the system at a given instant. While these systems work well for their intended applications, even the academic prices are prohibitive for integration into inexpensive UAVs. Additionally, the source code is not made available, and users of the systems are forced to accept the filter/algorithm performance of the systems as they are given.

Recently, due to the high-availability of low-cost sensing chips, many consumer-level devices such as the Apple iPhone, Nintendo Wii and Sony PlayStation 3 have integrated accelerometers into their hardware for more immersive user-experiences. Several chip manufactures are producing 3-axis accelerometers, however, the availability of integrated 3-axis roll-rate gyro chips is not as broad. Analog Devices, inc. is, at the time of this writing, the only company producing fully-integrated 6-degree-of-
freedom sensor units [1].

In any navigation system, performance and reliability are primary design drivers. In the world of small UAVs, size, weight and price are also of very high importance.

AggieNav is a unique design of cutting-edge sensing, power and processing hardware, paired with highly sophisticated data filtering algorithms, giving it a decisive lead in front of other similar systems.

AggieNav has a unique feature set not found on other INS solutions:

- Full high-accuracy 6-Degree-of-Freedom IMU
- Full 3-axis tilt-compensated compass
- Universal interface with any GPS unit via a serial port
- Dual pressure sensors for static and dynamic air pressures
- 72 MIPS onboard processing
- Onboard hardware mounts for a 600MHz Gumstix Linux computer, and Paparazzi [2] based autopilot system ("AggiePilot") for a full UAV system
- Lowest price for any such system
- Open software architecture allows AggieNav to be customized or augmented easily
- Weight: 70g, power: 1.0W total with Gumstix and GPS

1 AGGIENAV SYSTEM DESCRIPTION

AggieNav (Figures 2 and 3) has a combination of sensors to support high quality flight navigation. Primarily, if course, is the Analog Devices ADIS16354 Inertial Measurement Unit, with 6 full axis of roll-rate and accelerometer data. A Honeywell HMC6343 tilt-compensated magnetic compass provides slower, but accurate, filtered, absolute heading data. A high-rate civilian GPS receiver, in this case a 4Hz uBlox LEA-5H unit, provides lower bandwidth data about the UAV’s global position. Finally, two small yet accurate pressure sensors (SCP-1000 series) from VTI give both static and dynamic pressure, allowing for the calculation of both absolute elevation (with launch time calibration) and windspeed (differential via Pitot tube [3]). The power system is designed for the full voltage range of the batteries in the UAVs, and provides additional power to the Gumstix computer and the onboard host-mode mini-USB port.

2 FLEXIBLE COMPUTING: GUMSTIX

The Gumstix Verdex unit mounted on AggieNav (Figures 1 and 2) is used as a co-processor for the extensive filter computations, as well as control of other aspects of the UAV mission including control of payload and downlinking of mission data. With small redesign efforts, the AggieNav system can support the newer line of Gumstix—the Overo Earth, Wind, Water, and Fire. The Overo line is capable of up to 1200 Dhrystone MIPS, and the Overo Water even more, with an integrated C64x+ digital signal processor (DSP) core. Thus, AggieNav can support the future of small UAV navigation and attitude estimation algorithms.

3 UAV ATTITUDE ESTIMATION

AggieNav provides three axis gyro, accelerometer, magnetic heading sensor and GPS outputs. The main application of Ag-
Table 1. AGGIENAV VS OTHER SMALL UAV INS SOLUTIONS

<table>
<thead>
<tr>
<th>INS Unit</th>
<th>AggieNav</th>
<th>Stock Microstran 3DM GX2</th>
<th>Crossbow MNAV</th>
<th>Procerus Kestrel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max Gyro Bandwidth</td>
<td>700Hz (unfiltered)</td>
<td>250Hz</td>
<td>25Hz</td>
<td>9Hz</td>
</tr>
<tr>
<td>Max Gyro Dynamic Range</td>
<td>±300deg/sec</td>
<td>±300deg/sec standard</td>
<td>±150deg/sec</td>
<td>±300deg/sec</td>
</tr>
<tr>
<td>Accelerometer Dynamic Range</td>
<td>±10g</td>
<td>±5g</td>
<td>±2g</td>
<td>±10g</td>
</tr>
<tr>
<td>Accelerometer Resolution</td>
<td>14bit</td>
<td>16bit</td>
<td>NA</td>
<td>14bit</td>
</tr>
<tr>
<td>Accelerometer Bandwidth</td>
<td>700Hz (unfiltered)</td>
<td>250Hz</td>
<td>25Hz</td>
<td>9Hz</td>
</tr>
<tr>
<td>Magnetics Rate</td>
<td>5Hz heading solution</td>
<td>250Hz</td>
<td>1-100Hz</td>
<td>NA</td>
</tr>
<tr>
<td>Magnetics Accuracy</td>
<td>±3deg</td>
<td>0.001Gauss</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>GPS Rate</td>
<td>4Hz</td>
<td>No GPS</td>
<td>4Hz</td>
<td>NA</td>
</tr>
<tr>
<td>Max GPS Accuracy</td>
<td>2.5m</td>
<td>No GPS</td>
<td>3m</td>
<td>5m</td>
</tr>
<tr>
<td>Pressure Rate</td>
<td>1.8Hz</td>
<td>No Pressure</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Pressure Accuracy (Abs)</td>
<td>1.5Pa</td>
<td>470mW (minimum)</td>
<td>400mW</td>
<td>2.44Pa</td>
</tr>
<tr>
<td>Power Draw</td>
<td>600mW</td>
<td>470mW (minimum)</td>
<td>700mW</td>
<td></td>
</tr>
</tbody>
</table>

3.1 ATTITUDE REPRESENTATION

There are several methods to represent the orientation of a 3D rigid body in the inertial frame including Euler angle, directional cosine matrix, and unit quaternion etc. The most commonly used one is Euler angle (roll, φ, pitch, θ, and yaw, ψ). The trajectory control of an unmanned aerial vehicle can be converted to cascaded control of roll, pitch, and yaw. However, Euler angle has some singularity points. Unit quaternion provides another representation without introducing a gimbal lock problem. Unit quaternion could be defined as follows:

\[
q = \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix}, \quad \text{where} \quad q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1. \tag{1}
\]

The conversion from unit quaternion to Euler angles can be written as:

\[
\phi = \arctan\frac{2(q_2q_3 + q_0q_1)}{q_0^2 - q_1^2 - q_2^2 + q_3^2}, \tag{2}
\]

\[
\theta = \arcsin(-2(q_1q_3 - q_0q_2)), \tag{3}
\]

\[
\psi = \arctan\frac{2(q_1q_2 + q_0q_3)}{q_0^2 + q_1^2 - q_2^2 - q_3^2}. \tag{4}
\]
3.2 IMPLEMENTATION OF AN EXTENDED KALMAN FILTER (EKF)

Given a nonlinear system, an extended Kalman filter could be designed [10]. Assume the simplified nonlinear model is:

\[ x_k = f(x_{k-1}, u_k) + w_k, \quad y_k = g(x_k) + v_k. \]

where \( x_k \) is the system state vector, \( u_k \) is the system input vector, \( y_k \) is the system measurement vector, \( w_k \) is the process white noise with the distribution \( w_k \sim N(0, Q) \), \( v_k \) is the observation white noise with the distribution \( v_k \sim N(0, R) \).

The key idea of Kalman filter is to fuse the estimates of system states from both the system equation and measurement equation. The recursive structure of Kalman filter also makes it robust to the system changes. To start the Kalman filter estimation, the initial values need to set including \( Q \), \( R \) and \( P_{0|0} \). The Kalman filter predict and update steps include:

\[
\begin{align*}
\hat{x}_{k|k-1} &= f(x_{k-1|k-1}, u_k), \\
P_{k|k-1} &= F_k P_{k-1|k-1} F_k^T + Q_k, \\
\hat{y}_k &= y_k - g(x_{k|k-1}), \\
K_k &= P_{k|k-1} G_k^T (G_k P_{k|k-1} G_k^T + R_k)^{-1}, \\
\hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k (y_k - \hat{y}_k), \\
P_{k|k} &= (I - K_k G_k) P_{k|k-1},
\end{align*}
\]

where

\[
F_k = \frac{\partial f}{\partial x}|_{\hat{x}_{k-1|k-1}, u_k}, \quad G_k = \frac{\partial g}{\partial x}|_{\hat{x}_{k-1|k-1}}.
\]

3.3 ATTITUDE ESTIMATION USING EKF

Assume the system state is a vector \( q \), representing the unit quaternion and the gyro bias and the system output is a vector \( \hat{y} \), representing the acceleration data [9]:

\[
q = \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix}, \quad y = \begin{bmatrix} a_x \\ a_y \\ a_z \\ b_p \\ b_q \\ b_r \end{bmatrix}.
\]

Assume \( p \) is the gyro measurement from the roll axis, \( q \) is the gyro measurement from the pitch axis, and \( r \) is the gyro measurement from the yaw axis, the nonlinear system can be modeled by [9]:

\[
\dot{q} = \begin{bmatrix} 0 & -\dot{\rho} & -\dot{\phi} & 0 & 0 \\ \dot{\rho} & 0 & -\dot{\phi} & 0 & 0 \\ \dot{\phi} & \dot{\rho} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} q + w_k, \quad w_k \sim N(0, Q),
\]

\[
\hat{y} = \begin{bmatrix} 2q_1q_3 - q_0q_2 \\ 2q_2q_3 + q_0q_1 \\ g(q_0^2 - q_1^2 - q_2^2 + q_3^2) \end{bmatrix} + v_k, \quad v_k \sim N(0, R),
\]

where

\[
\begin{bmatrix} \dot{\rho} \\ \dot{\phi} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} p \\ q \\ r \end{bmatrix} - \begin{bmatrix} b_p \\ b_q \\ b_r \end{bmatrix}.
\]

It needs to be pointed out that Eqn. 11 is an approximation close to the static case since only the gravity is considered for accelerometer measurements. It is true when the UAV is not accelerating too much. But a more general dynamic case could be represented as follows [6]:

\[
\hat{y} = \begin{bmatrix} q_0v_0 \sin \theta + \sin \theta \\ v_p \cos \theta - p_s \sin \theta - \cos \theta \sin \phi \\ -v_q \cos \theta - q_s \cos \theta \cos \phi \end{bmatrix} + v_k, \quad v_k \sim N(0, R),
\]

where \( v_0 \) is the 3D speed measured by GPS. Due to the time limit, Eqn 11 is used in our experiments. The attitude state estimation can be calculated using the steps described in Sec.3.2.

4 EXPERIMENTAL RESULTS

4.1 RAW SENSOR DATA COMPARISON

The raw sensor data from AggieNav is compared with the sensor data from Microstrain Gx2 IMU, which is an expensive IMU with 3-axis gyro, accelerometer and magnetic sensors. The AggieNav data is scaled to the same unit as Gx2 IMU. The gyro data is shown in the unit of degree/s and the acceleration data is shown in the unit of m/s².
Figure 4. Gyro Sensor Comparison

Figure 5. Acceleration Sensor Comparison
4.2 PRELIMINARY RESULTS FOR ATTITUDE ESTIMATION USING KALMAN FILTER

The preliminary EKF is designed based on the descriptions above with no heading corrections due to the magnetic sensor interpretation problems. The EKF is set to run at 100hz.

From the figures above, we can see that the roll and pitch angles can be estimated with the current EKF although there is obvious high frequency noise. The problems left are the prefiltering for the raw sensor data and Kalman filter covariance matrix estimation.

5 CONCLUSION

In this paper we have presented a high-performance Extended Kalman Filter, running with AggieNav, a collection of high-quality, low cost sensors for UAV attitude estimation. Along with a comparison with other lower-cost UAV navigation systems, the theory and design of the EKF is shown, and results on real-world data have been presented. The future of the project involves further development of the dynamic cases, and more flight testing using the hardware as the navigation reference.

ACKNOWLEDGMENT

The author would like to thank all of CSOIS, Yiding Han, Austin Jensen, as well as the Utah Water Lab and the Association for Unmanned Vehicle Systems International (AUVSI) for their Student UAS competitions. This work has been supported by Utah Water Research Laboratory MLF funding (2006-2010).

REFERENCES