Research on the state of estimation for unmanned research and rescue helicopter

JingHeng Wang[1, a], Wei Zhao[1],DongQi Meng[1]

[1] Department of Aviation Life-saving

Aviation University of Air Force

Changchun 130022，China

[a] email：hlwswlg@163.com

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Abstract. This paper presents a technique to accurately estimate the state of unmanned research and rescue helicopter, Two Kalman filters were used, one for the gyroscope data and the other for the accelerometer data. Our approach is unique because it explicitly avoids dynamic modeling of the system and allows for an elegant combination of sensor data available at different frequencies. We also describe the larger context in which this work is embedded, namely the design and implementation of an unmanned research and rescue helicopter.

Introduction

State estimation is a fundamental need for unmanned research and rescue helicopter. We have recently begun an effort to develop algorithms that can accurately estimate the state of an unmanned helicopter in order to improve the functioning of the control algorithms being developed as part of the work described above. In the paper we report on the first results from this effort. Given the overhead of flight experimentation, we have taken a two staged approach to the problem of state estimation. In the first stage we test our algorithm in simulation, using a simulated model of a full-scale helicopter as well as a nonlinear controller that can stabilize it. Based on the encouraging results thus far, we plan to implement our algorithm on the physical system over the next few months.

The method to estimate the state of a helicopter is to use a model. If a state-space helicopter model is available, a Kalman filter based estimator can be built using the model. However the main drawback of this approach is that it is difficult to obtain a good helicopter model. Furthermore, the dynamics of a helicopter are expressed as a set of nonlinear equations. This makes it difficult to construct a Kalman filter. The other method to estimate state is to use a sensor model. The advantage of this is that a complex helicopter model is not needed. Further, Kalman filter need not be rebuilt for each different unmanned helicopter if the sensor suite is unchanged. In this paper we use the second approach in estimating the state of a helicopter controller.

Helicopter Model

There are six rigid body degrees of freedom in the helicopter; three translational and three rotational. The equations of helicopter dynamics are expressed with respect to the body axis coordinate system. The attitude of the body with respect to the inertial reference frame is defined by Euler angles: θ,ϕ,φ .The order of rotation is as follows: first, rotate along the X-axis by angle ϕ, then, along the Y-axis by angle θ ,and finally along the Z-axis by angle φ . To each such unique order there exists a corresponding rotation matrix which transforms vectors in the body-centered frame to the inertial fame. The general equations of motion of a helicopter can be found in any standard textbook [3] on the dynamics. The model includes the main rotor rigid body effects, coning and quasi-steady flapping. This model has been used extensively in helicopter flight control system.

In the simulated model, there are four control inputs available to the pilot. These are called collective (θ_o), longitudinal cyclic (θ_{ls}), and lateral cyclic (θ_{lc}), which are control inputs for the main rotor, and tail-rotor collective (θ_{ot}), which is for the tail rotor. Four reference commands are given: θ, ϕ, φ and h.

The outputs of helicopter with commands $\theta = 20^{\circ}$, $\phi = 30^{\circ}$ $\varphi = 0$ and $h = 0$ are shown in Fig. 1when there is no noise corruption and no Kalman filter in the loop. This “baseline” figure shows the operation of the controller before we began our experiments. We used these values of command signals throughout the simulation in comparing outputs.

To test the sensor-noise refection capability of our filters, we infected noise into the baseline simulation and added an estimator which reconstructs the state based on these noisy measurements. As we show later, the filters are able to reject fairly realistic levels of noise that may be expected in real flight operations.

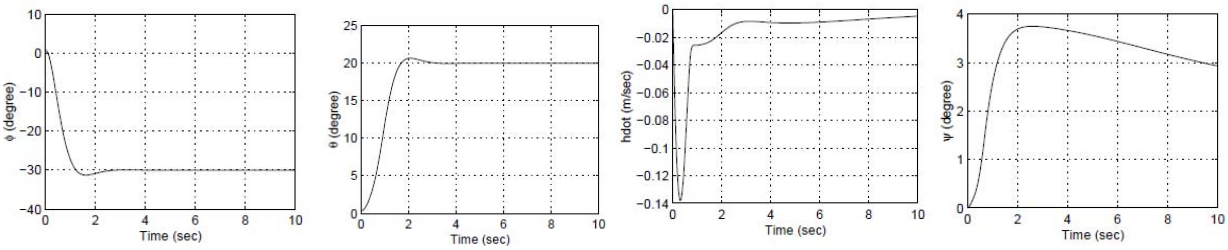

Figure 1: Outputs of helicopter state without noise or Kalman filtering

Noise Model and Characteristics

The AVATER unmanned helicopter currently has three gyroscopes, three accelerometers, a compass and a GPS unit. The gyroscopes, accelerometers and GPS are part of an integrated avionics. We plan to add two inclinometers to directly measure the roll and the pitch as well. The gyroscopes in the avionics unit are Systron Donner Quartz Gyros whose noise profile is well known.

The key difficulty in attitude estimation using gyroscopes is the low frequency noise component, which is also referred as bias that violates the white noise assumption needed for standard Kalman filtering. The model assumes that the gyro noise consists of two elements: rate noise $n_r(t)$ and a rate random walk $n_w(t)$. We used the Systron Donner Quartz Gyro for numerical values for noise intensities. The intensities calculated from experiments were $\sigma_r = \sqrt{N_r} = 0.009(\text{deg/sec})/\sqrt{H_z}$ and $\sigma_w = \sqrt{N_w} = 0.005012(\text{deg/sec})/\sqrt{H_z}$. The level of noise in the compass and inclinometers is assumed to be $\sigma_{ss} = 0.01$. The noise associated with measuring accelerations from the accelerometers and the positions from the GPS is assumed to be white. We used $\sigma_r = 0.07(m)$ for the noise associated with the GPS and $\sigma_q = 0.05(m/\text{sec})$ for the accelerometers.

Architectures of Kalman Filter

A Kalman filter model for acceleration is well described in [2]. That approach was followed here for building the filter associated with the accelerometers. Our simulation uses three components of acceleration, so we use the appropriate rotation matrix and transform the acceleration data with respect to the body reference frame to the acceleration with respect to the inertial reference frame. The rotation matrix can be calculated by using the Euler angles.

For simplicity, we describe a one dimensional Kalman filter here. Let the noise w be a white Gaussian noise of mean zero and variance kernel $E\{w(t)w(t+\tau)\} = Q\delta(\tau)$ entering at the acceleration level. Let the noise v be a white Gaussian noise of mean zero and variance $E\{w(t)w(t+\tau)\} = R_C\delta(\tau)$ which happens in measuring position r_t, where subscript t denotes a true value. The two error states are defined as

$$\delta r(t) = r_m(t) - r_t(t) \qquad (1)$$

$$\delta u(t) = u_m(t) - u_t(t) \quad (2)$$

Where u velocity and subscript is m denotes a measured quantity. Then we can write the following state equation.

$$\begin{bmatrix} \dot{r}_i(t) \\ \dot{u}_i(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} r_i(t) \\ u_i(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} (a_t(t) + w(t)) \quad (3)$$

The state equation of the true position, velocity and acceleration is:

$$\begin{bmatrix} \dot{r}_t(t) \\ \dot{u}_t(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} r_t(t) \\ u_t(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} a_t(t) \quad (4)$$

Subtracting Equation 4 from Equation 3, we have

$$\begin{bmatrix} \dot{\delta}_{rt}(t) \\ \dot{\delta}_{ut}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \delta_{rt}(t) \\ \delta_{ut}(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} w(t) \quad (5)$$

From these equations, the steady state values can be obtained by solving $\dot{P}(t) = 0$

$$P = \begin{bmatrix} \sqrt{2}Q^{1/4}R_c^{3/4} & Q^{1/2}R_c^{1/2} \\ Q^{1/2}R_c^{1/2} & \sqrt{2}Q^{3/4}R_c^{1/4} \end{bmatrix} \quad (6)$$

We used Euler parameters in representing the three dimensional attitude. We can easily calculate the rotation matrix from Euler parameters. We define $q_{k/k}(\vec{b}_{k/k})$ to be the quaternion (bias) estimate at time t_k based on data up to and including $z(t_k)$, $q_{k/k-1}(\vec{b}_{k/k-1})$ the quaternion (bias) estimate at time t_{k-1} propagated to t_k, right before the measurement update at t_k. The estimated angular velocity defined as:

$$\vec{w}_{k/k-1} = \vec{w}_m(t_k) - \vec{b}_{k/k-1} \quad (8)$$

The full estimated quaternion is propagated over the interval $\Delta t_k = t_k - t_{k-1}$ according to the following equation:

$$q_{k/k-1} = (e^{1/2\Omega(\vec{w}_{avg})\Delta t_k} + (\Omega(\vec{w}_{k/k-1})\Omega(\vec{w}_{k-1/k-1}) - \Omega(\vec{w}_{k-1/k-1})\Omega(\vec{w}_{k/k-1}))\Delta t_k^2 / 48) q_{k-1/k-1} \quad (9)$$

The equation for error state covariance propagation, the Kalman gain matrix, the updated covariance and the updated error state are given by:

$$P_{k/k-1} = \Phi(k,k-1)P_{k-1/k-1}\Phi^T(k,k-1) + Q_k, \quad (10)$$

$$K_k = P_{k/k-1}H_k^T(H_K P_{K/K-1}H_k^T + R_k)^{-1}, \quad (11)$$

$$P_{k/k} = P_{k/k-1} - K_k H_k P_{k/k-1}, \quad (12)$$

Simulation Results

As mentioned above, nine states were considered and two filters were used to process the data stream from the helicopter's sensors in the simulations reported here. We used $\theta = 20°$, $\phi = -30°$, $\dot{\varphi} = 0$ and $\dot{h} = 0$ as reference commands.

Consider Fig.2 This figure shows the value of the real quaternion element q_4, estimated quaternion q_4, measured quaternion q_4 and dead-reckoning estimate of element q_4. As can be seen from the plot, the Kalman filter estimates the real quaternion well from the measured data corrupted by noise. We can also see that the dead-reckoning quaternion is a very good estimate of the real quaternion. The level of noise in angular velocity is very low. Therefore, it is natural that the dead-reckoning quaternion calculated from measured angular velocity is good estimate of 3-D attitude. However, this is good only for a small time span. Due to the integrating factor, error is accumulated and becomes large after a long time if there is no correction.

Fig.3 shows fore error plots; the difference between real position and filtered position data, the difference between real position and dead-reckoning position, the difference between real velocity and filtered velocity, and the difference between real velocity and dead-reckoning velocity. The filtered data for velocity is obtained from adding the value of estimated error state of velocity to the value that we get by integrating the measured acceleration. Care must be taken to use the appropriate coordinate system in calculating filtered and dead-reckoned velocity. The estimated attitude $(\theta_e, \phi_e, \varphi_e)$ was use to get the rotation matrix in processing filtered velocity and the dead-reckoning attitude $(\theta_d, \phi_d, \varphi_d)$ was used to calculate dead-reckoning velocity and position.

The performance improvement can be seen by feeding filtered data to the controller instead of using raw sensor data. The dotted line in Fig.4 denotes the output of the helicopter when raw sensor data was fed to the controller. The solid line is the output when filtered data was used for controller input. As can be seen from the plot, the motion is more stable when the controller used filtered data despite larger overshoot.

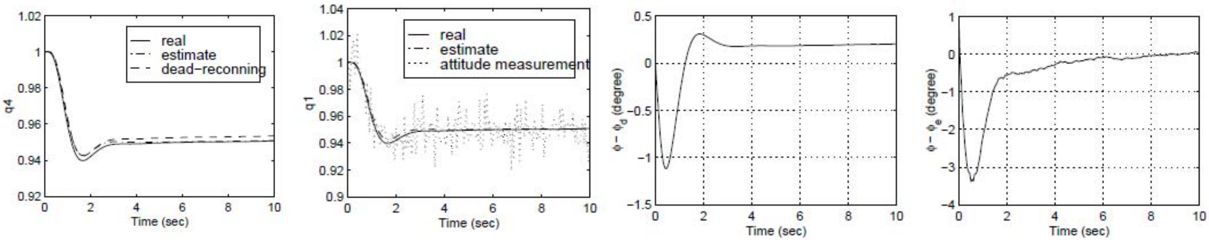

Figure 2: The values of real, filtered, measuredand dead-reckoningquaternion element q_4 , difference between the real and filter, and difference between real and dead-reckoned

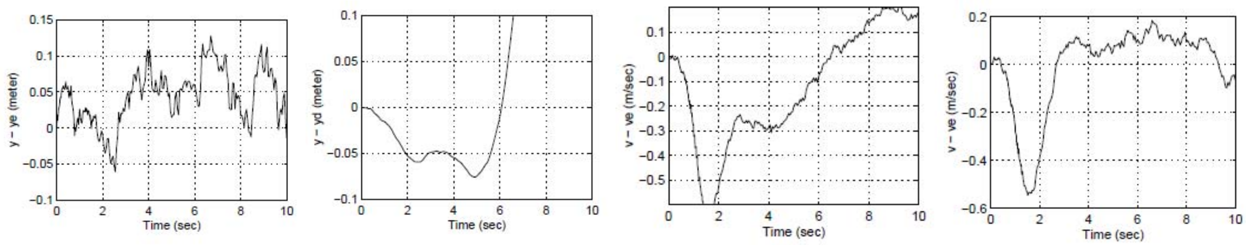

Figure 3: Error in position y hen the Kalman filter was usedand when dead-reckoning was used, and error in velocity v when the Kalman filter was used and dead-reckoning was used

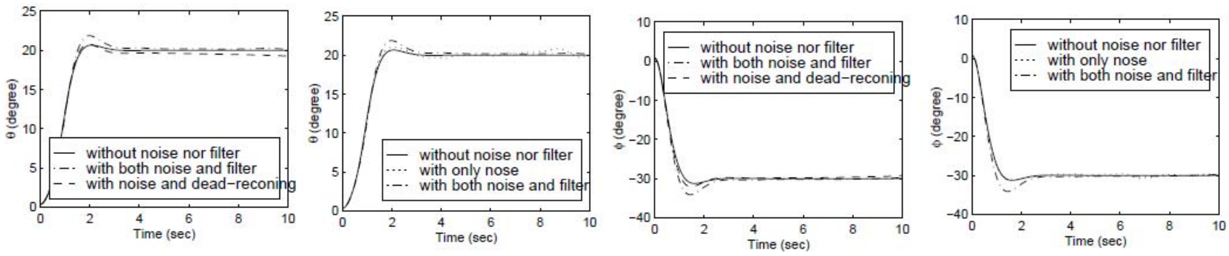

Figure 4: Output θ and ϕ of the helicopter when there is no noise nor filter, when there is additive noise and no filter, when we use two Kalman filters in noisy environment, when we use dead-reckoning attitudes without a Kalman filter

Conclusions and Future Work

In this paper, a state estimator is developed for unmanned research and rescue helicopter without using a helicopter model. We would like to emphasize that the controller used in the test here is model based but not the estimator. The validity of our approach was verified by feeding filtered data to the controller and observing the output of the helicopter. It remains as future work to verify that our filter also work well when we change the controller or helicopter without modifying the sensors. After evaluating our Kalman filters for several helicopter models and controllers, our ultimate goal is to implement our algorithm on the real unmanned helicopter for researching and rescue.

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