Navigation system design for RUAVs Based on a Novel KALMAN Filter

Chong Wu1,2, Dalei Song1, Juntong Qi1, Jianda Han1, and Zelin Shi1
1. Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang, Liaoning, 110016 China
2. Graduate School of the Chinese Academy of Sciences, Beijing, 100080 China

Abstract: GPS/INS navigation system is necessary for realizing the accurate and autonomous control of the rotorcraft unmanned aerial vehicles (RUAVs). However, because of the intrinsic time delay of the velocity measurement from the GPS and the noisy acceleration measurement caused by the strong vibration on the RUAV, the traditional navigation system’s estimation often cannot be applied for online flight controllers as feedback value on RUAVs. In this paper, a new algorithm of data fusion is proposed to eliminate the time delay of velocity and the noise of acceleration. Based on the simplified reference model of GPS/INS system, a two-step kalman filter is used to estimate the acceleration bias and fusion the INS and GPS data to obtain the accurate measurement for the body moving of the RUAVs. Based on the ServoHeli-40 RUAV platform, flight tests have been done to verify the validity of the data fusion algorithm.

Key Words: RUAV, Navigation, Extended Kalman Filter, Time-Delay Compensation

I. INTRODUCTION

Rotorcraft unmanned aerial vehicles (RUAV), with the versatility in maneuverability of vertical taking off/landing, hovering, lateral flight, pirouette, and bank-to-turn, can be utilized in various applications, either in military or civil [1]. Whereas the complexity of the RUAV in both mechanism and control system design have delayed the application of RUAV. Many researchers have been involved in building a more capable RUAV system in the application.

The navigation system is a crucial part in the design of a flight control system for the RUAV; accurate navigation information about the flight state would improve the accuracy of the control system. Many algorithms in navigation have been proposed [2]-[5]; most of them were verified by simulation, but seldom implemented due to the complexity and limitation of simulation. On the other hand, the limitations in payload, cost, size, and processor speed also limit the implementation of some methods. Therefore, a low-cost, small sized, compact navigation system with a high processing speed is necessary in the research of advanced navigation theory. In [6], we built a compact, low-cost, small sized navigation system; while when we apply this system in some other small-sized rotorcrafts, we found that it doesn’t work very well. After the analysis we made the conclusion that the vibration on the airframe and the time-delay of GPS velocity measurement receiver are the causation of the malfunction of navigation system.

In this paper, we will concern with the airframe vibration and velocity measurement latency. In most paper [6] [10], to eliminate the vibration of the acceleration, low-pass filter or notch filter is used. As to the time-delay of GPS velocity, in [7]-[9], they consider the GPS velocity time-delay as measurement latency in the kalman filter framework and many algorithms have been proposed. On the other hand, we can simply consider the GPS velocity measurement as a time-delay signal, and then we can try to compensate the latency by some polynomial predictive filters.

In this paper, we will propose an algorithm we call it polynomial predictive kalman filter to compensate the latency of velocity measurement, a band-stop filter is designed to eliminate the vibration of acceleration. A two-stage EKF is implemented to estimate the flight state. Flight test verify
the validity the efficiency of the algorithms.

The velocity measurement lag compensation algorithm is proposed in section II. In Section III, a band-stop filter is designed for the acceleration measurement vibration elimination. The experimental test and results are presented in Section IV. Further research is discussed in the conclusion in Section V.

II. VELOCITY MEASUREMENT LAG COMPENSATION

In our avionics system, a U-blox LEA-5H is employed to provide latitude, longitude, altitude and three-axis velocities respectively in north, east and down. With an update rate of 5Hz, the GPS receiver has a 100 ms latency [11] which may lead to the malfunction of the navigation system in some time-critical environments. To compensate the measurement lag from GPS-receiver without noise magnifying, at the same time, to decrease the calculation load the algorithm, a polynomial predictive kalman filter is proposed to settle this problem.

The polynomial predictive filter [11-13] is based an simple assumption that the signal \( x_k \) should can be modeled as a polynomial of degree \( L \), as in (1).

\[
x_k = a_0 + a_1 k + \cdots + a_L k^L = \sum_{i=0}^{L} a_i k^i
\]

The FIR-filter-based polynomial predictor (2) can be derived by fitting the \( L \) degree polynomial model through \( M \) latest samples of the input signal.

\[
\hat{x}_{k+N} = \sum_{m=0}^{M} h_m x_{k-m}
\]

\( N \) is the prediction steps, \( M \) is the predictor length, \( L \) is the degree of the polynomial model.

It turn out that the predictor’s coefficients are independent of the input signal and are just depend on \( N, M \) and \( L \). By substituting (2) into (1), we can a polynomial equation in (3).

\[
[-N] = \sum_{m=0}^{M-1} h_m m^l \quad l = 1 \cdots L
\]

Generally, we have \( M \geq L \), and we have extra degrees of freedom which can be used to minimizing the white-noise gain \( NG = \sum_{m=0}^{M-1} |h_m|^2 \). Then the coefficients can be obtained by solving the Lagrange function in (4).

\[
\Phi(h_0, \cdots, h_{M-1}, \lambda_0, \cdots, \lambda_L) = \sum_{m=0}^{M-1} |h_m|^2 + \lambda_0 \left[ \sum_{m=0}^{L} h_m m^l - [-N]^l \right]
\]

With the given \( N, M \) and \( L \), we can get the coefficients \( h_m \). After measurement and simulation of the real signal of GPS velocity, we set the proper parameters as \( N = 1, L = 2, M = 3 \), and we can obtain the coefficients as \( h_0 = 3, h_1 = -3, h_2 = 1 \). Then we obtain a proper polynomial predictive filter as (5).

\[
\hat{x}_{k+1} = 3x_k - 3x_{k-1} + x_{k-2}
\]

A simple polynomial predictive filter can’t take the polynomial model error in consideration; at the same time, it would magnify the noise gain even though it has a predictive function. To tackle these problems, a kalman filter is built based on the polynomial predictive filter.

We define \( \vec{x}_k = [x_k \quad x_{k-1} \quad x_{k-2}]^T \), \( \vec{y}_k = [y_k \quad y_{k-1} \quad y_{k-2}]^T \), a state space equation can be obtained as (6).
\[
\begin{align*}
\bar{X}_{k+1} &= \begin{bmatrix} 3 & -3 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \bar{X}_k + \begin{bmatrix} w_x \\ 0 \\ 0 \end{bmatrix} \\
\bar{Y}_k &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \bar{X}_k + \begin{bmatrix} v_x \\ v_{x-1} \\ v_{x-2} \end{bmatrix}
\end{align*}
\tag{6}
\]

\(w_x\) is the polynomial model error covariance and \(v_x\) is the measurement covariance. With the state space equation in (6), we employ the standard linear kalman filter. Actually the real signal can’t be modeled as a polynomial perfectly, so the \(w_x\) is important to take this model error in consideration and with a proper choice of the \(w_x\), the model error can be compensated by the kalman filter. At the same time, the simple polynomial predictive filter take the measurement without any preprocess and ignore the measurement error, here in kalman filter framework, this also can be taken into account. Theoretically, we can expect a more accurate estimation of the velocity with measurement prediction and noise reduction. That’s what we called polynomial predictive kalman filter.

In Fig.1, we compare the simulation result of three different predictive filters: Polynomial Predictive Kalman Filter (PPKF), Recursively Linear Smoothed Newton Filter (RLSN), Normal Differential Kalman Filter (KF). As we can see, the RLSN can make some prediction while it will magnify the noise gain; the KF can smooth the noise while it will introduce more time-lag of measurement; the PPKF has better prediction without magnify the noise gain.

III. ACCELERATION MEASUREMENT VIBRATION ELIMINATION

Vibration problem is one of the most important matter that should be considered when introducing a controller to a rotorcraft, the measured acceleration would be contaminated because of the vibration,
even worse, the signal would be totally be polluted that can’t be used at all. As we can see in Fig.2, the acceleration’s measurement is of no sense at all without any preprocessing.

To eliminate the vibration’s impact, we can try to add more damping to isolate the vibration from the fuselage. On the other hand, we can try to extract the real signals from the measurement by the digital process algorithms such as low-pass filter or band-stop filter. Low-pass filter can introduce time-lag because of its intrinsic property. Fig.3 is the FFT frequency spectrum of x-axis acceleration measurement with a sample rate of 100 Hz; as we can see, there is a high frequency element in 20.55 Hz; such a frequency is mainly introduced by the main-rotor’s rotation with a rotation speed of 1230 revolutions per minute (rpm).

A band-stop filter is proposed here to eliminate the vibration caused by main-rotor’s rotation, with the help of the filter design tool in Matlab, we can get a band-stop filter with the magnitude-frequency characteristics as shown in Fig.4 (a). Fig.4 (b) is the power spectrum of the measurement and the result after band-stop filter, the vibration of 20.5 Hz has been deleted effectively.
To validate the algorithms proposed above, we embedded these algorithms into the navigation system we built before [6]. This navigation system was designed and implemented on an ARM9 LPC3250 platform, based on the characteristics of the sensors, a two-stage Extended Kalman Filter (EKF) is embedded to estimate the flight states, get rid of online noise, and fed back the results to the flight controller. The full system has been tested on a ServorHeli-40 RUAV platform. Fig. 5 is the framework of the navigation system and its realization.

An EKF with full state of navigation variables would be proper, whereas the calculation load would be too large. A two-stage KF is implemented here: an EKF is implemented to estimate the attitude and another EKF is used to estimate the velocity and accelerate bias. First, the attitude is estimated, and then the velocity is estimated based on the result of the attitude estimation. Such a design is based on the fact that the variation of attitude is faster than velocity, so we can make an assumption that the attitude would be still when the velocity is changing. State equation of the two-stage kalman filter is presented as in (7).
AUVSI’s Unmanned Systems North America 2011

\[
\begin{bmatrix}
\dot{\phi} \\
\dot{\theta} \\
\dot{\psi}
\end{bmatrix}
= \begin{bmatrix}
(qC_\phi - rS_\phi)\tan_\phi \\
-qS_\phi - rC_\phi \\
(qC_\phi - rS_\phi)/C_\theta \\
(qC_\phi + rC_\phi)/(C_\phi C_\theta S_\phi)
\end{bmatrix} \left/ \begin{bmatrix}
C_\phi C_\theta \\
C_\phi S_\phi \\
C_\phi C_\theta S_\phi \\
C_\phi S_\phi S_\theta
\end{bmatrix} \right. \begin{bmatrix}
\phi \\
\theta \\
\psi
\end{bmatrix} + w_a
\]

\[
Y_{\text{angle}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix} + v_a
\]

\[
\begin{bmatrix}
\ddot{u} \\
\ddot{v}
\end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ a_{\text{bias}} \end{bmatrix} + \begin{bmatrix} R_\alpha \\ 0 \end{bmatrix} \alpha + w_v
\]

\[
Y_v = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \begin{bmatrix} u \\ a_{\text{bias}} \end{bmatrix} + v_v
\]

\[
R_\alpha = \begin{bmatrix}
c_{\phi \psi} & c_{\phi \theta} & -c_\phi \\
-s_{\phi \theta} & c_{\phi \theta} & s_\phi \\
-s_{\phi \psi} & c_{\phi \psi} & s_\phi c_\theta
\end{bmatrix}
\]

(7)

We can easily embed the algorithms proposed in this paper into the navigation system, the framework is shown in Fig.6. The acceleration is preprocessed through a band-stop filter designed in section III, the velocity is preprocessed through a PPKF designed in section II, then the two-stage kalman filter is executed.

To verify the validity of the data fusion algorithm, flight test of hovering control and waypoint control is executed. Fig.7 is the way point flight trajectory compared with the predefined trajectory, Fig.8 is the deviation of the flight test in hovering and waypoint mode respectively. As we can see, the RUAV can effectively track the predefined trajectory with a deviation within 2m. In hovering control mode, the RUAV can hover at the predefined point with a deviation within 1m. These flight tests validate the validity of the flight control system, at the same time, validate the validity of the navigation system.
V. CONCLUSION

In this paper, a polynomial predictive kalman filter is proposed to compensate the GPS velocity measurement lag, a band-stop filter is designed to eliminate the vibration of the main-rotor rotation. Simulation compare has been made among the PPKF, KF and RLSN. Then the PPKF and the band-stop filter is embedded into the pre-built navigation system, the flight tests show the validity of the system and algorithm.

We believe that the improvement of the navigation system is mainly relying on the preprocessing algorithms of the measurement. In this paper, it’s the first time we take our concentration on the measurement preprocessing, a PPKF is proposed but less theoretical analysis has been made, the polynomial predictive filter model’s error may be considered more carefully and improvement can be made in this part.

ACKNOWLEDGMENT

The work reported in this paper was funded under the National Natural Science Foundation of China(61005086), Human’s brain decision characteristics based flight control method for flying-robot.
REFERENCE


