Algorithm Design of a Distributed Strap-down Inertial Navigation System for Unmanned Rotorcraft

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ABSTRACT

A strap-down inertial navigation system (SINS) is developed by using MESM sensors and designing efficient algorithms for unmanned aerial vehicle. The algorithms of attitude and heading reference system (AHRS) are proposed based on extended Kalman filter with quaternion orientation estimation and linear Kalman filter with integration of angular rates. The performance of the two different architectures of the attitude estimation algorithms are implemented and compared by experiments. The velocity and position estimation systems are obtained in terms of the rigid dynamic equations and GPS measurements. The advantage of the distributed and cascaded approaches of the SINS is that reducing the order of the filters and saving computational resource effectively. The reliability and applicability of the proposed algorithms are verified on a small unmanned tilt-rotor.

INTRODUCTION

In recent years, there are many small unmanned aerial vehicles (SUAVs) which have broad prospects in military and civil aviation industry. These autonomous SUAVs require on-board strapdown navigation system which offers flight attitude, velocity and position, and feedbacks sensing signal to control system. The SUAVs, with small payloads, high vibration environment and sensitive maneuverability, which require the measurement system has high-precision, small-size, light-weight, low-cost and low-power. In the past decade, the low-cost sensors based on micro electro-mechanical system are widely used in attitude and heading reference system (AHRS) for the SUAVs. However, the precision and resolution of these sensors are much lower than the traditional inertial components. So it is very challenged to achieve high accuracy. The outputs of the typical MEMS rate gyros subjected to noise, drift, random-walk and markov process on the array of 30°-150°/h error. Therefore, the multi-sensors information fusion technology is widely applied in the navigation estimation system [1-5], and the Kalman filter is the most brief and effective tool in using. Many successful solutions are implemented by using other inexpensive sensors such as accelerometers, magnetometers and GPS to correct the drift of rate gyros. The excellent performance is obtained. For example, [6] described a linear fusion algorithm for attitude estimation by using MEMS-based sensors. Unlike commonly used quaternion parameters or Euler angles for gyro-based systems, the Kalman filter state vector was constructed by tri-axial magnetic field and tri-axial earth gravity in the body frame. The process model was developed by using differential orientation cosine matrix, which represented the rotation from the earth frame to the body frame, and the
The measurement model was obtained by the output of the tri-axial accelerometer. The system presented in [7] utilized a tri-axial rate gyro with an aiding system which was mechanized using GPS or magnetometer and accelerometer. The Euler angle and quaternion-based Kalman filter structures were achieved. Then the effects of filtering accuracy were analyzed by regulating gain factors and estimator pole placement. Anthony Kim et al. presented a real-time quaternion-based orientation estimation system with three accelerometers and three rate gyros[8]. The process and measurement models were developed based on the relationship between quaternion, angular rate and the measurement of gravity from accelerometer. Experiments demonstrated that the Kalman filter tracked the orientation states quite accurately. More recent publications described the using of low-cost MEMS inertial and magnetic sensors constructing the AHRS with a robust and simple algorithm[9]. The robust performance about the algorithm was scheduling the filter's gain according to acceleration-based switch architecture.

As aircraft vehicles, especially autonomous SUAVs, the AHRS was indispensable for the inner loop flight control system within SAS and ACAH modes. The vehicles were augmented stability and controllability by feedback the angular rates or attitudes from the AHRS. The out loop usually contained velocity and position control loop, therefore, on the basis of the attitude angle estimation accuracy, the velocity and position estimation were also developed by designing algorithms. The velocity or position of the vehicles was mainly determined by three methods. The first one was to single or double integrated the output of the tri-axial accelerometer and converted the body frame to earth frame by attitude matrix, and the drift and noise about the accelerometer led to large deviation with the time. The second one was to utilize single point GPS with low update frequency, absolute error and avoiding drift error over time. Considering both merits of GPS and accelerometer had been directly towards the third one, which utilized the multi-sensors fusion technology constructed the SINS/GPS navigation system to improve navigation accuracy and reliability. GPS as an external aiding source for aligning the low-cost SINS in-motion was published in [10]. The robust Kalman filter was derived and the velocity information from the GPS was employed as a measurement to the filter. Bijker et al [11] proposed two small order extended Kalman filter for estimating the attitude, velocity and position in sequence of an airship. The attitude determination was developed by using MEMS gyros, the earth’s magnetic and gravity filed, meanwhile, the velocity and position estimation were updated from a loosely integrated GPS receiver. Tan et al designed a small (28g) low-cost GPS/IMU with the proposed Kalman filter based on complementary filter and enhanced the frequency response of the GPS or IMU individually [12]. It can be seen that the MEMS sensors and GPS have been extensively used in the SINS studies in order to improve the accuracy of the estimation system, and the algorithms designing are more important than the MEMS sensors themselves.

This paper attempt to design a distributed and low-order GPS/SINS for a small unmanned tilt-rotor aircraft. The MEMS sensors-based AHRS is developed into quaternion-based and angular rate integration process model in that comparing the efficiency and accuracy about the two schemes. The measurement model is made up with tri-axial acceleration of the gravity and tri-axial magnetic earth filed. The attitude quaternion is obtained through recursive filter rather than nonlinear
solution such as Gauss-Newton iteration. The angular rate integration method is a linear Kalman filter with low computational cost which made the iterative process easy to be implemented by using inexpensive microprocessors. After obtaining accurate attitude angles, the velocity estimation system can be developed according to rigid body equation of motion in terms of specific forces removal of gravity components [13], and the low-order velocity Kalman filter is constructed by using standard GPS receiver. Then, the position process model is achieved according to the relationship between velocity and position, and the measured process model also utilizes a standard GPS. As a result, the proposed GPS/SINS is simplified and can be executed at high rate using low-power microprocessors. Experiments are performed on a small unmanned tilt-rotor aircraft, and the results show the effectiveness of the proposed algorithms.

**ALGORITHM DESIGN OF ATTITUDE DETERMINATION**

**MEMS Sensors Error Models**

The AHRS is a complete inertial measured system that includes a tri-axial gyroscope, a tri-axial accelerometer, and a tri-axial magnetometer. The MEMS sensors are not perfect enough, in particular they are drifting over time enormous. The drift error sources usually contain determinacy error and random error. The determinacy error can be compensated by ways of sensors calibration. The random error of MEMS sensors includes angular white noise, angular random walk and rate random walk. The MEMS accelerometers and magnetic sensors have no long term drift accumulation, but the noise is too great from observing the gravity and geomagnetism. In order reduce filter order and computation, the MEMS gyro model contain random constant, first-order Markov and white noise within short time, the first-order Markov and white noise are considered of accelerometer and magnetometer, and the error models of the sensors are expressed as follow:

$$\begin{align*}
    \epsilon &= \epsilon_r + \epsilon_b + w_a, \dot{\epsilon}_r = -\frac{1}{T_g} \epsilon_r + \eta_g, \dot{\epsilon}_b = 0 \\
    \nabla &= \nabla_r + w_a, \nabla_r = -\frac{1}{T_a} \nabla_r + \eta_a \\
    \Delta &= \Delta_r + w_m, \Delta_r = -\frac{1}{T_m} \Delta_r + \eta_m
\end{align*} \tag{1}$$

where $\epsilon_r, \nabla_r$ and $\Delta_r$ are Markov process, $\epsilon_b$ is the random constant of gyro, $w_a, w_m$ and $w_m$ are uncorrelated white noise, $\eta_g, \eta_a$ and $\eta_m$ are driver noise, $T_g, T_a$ and $T_m$ are autocorrelation coefficients.

**Measurement Model**

It is widely known that there are many different solutions to measure the vehicle’s attitude, such as the integration of angular rate, measurement of the gravity component and tri-axial magnetic filed, multi-antenna of GPS proposal [14,15] or vision-based [16] et al. The most straight-forward way to observe the attitude is using accelerometer as an inclinometer to acquire roll and pitch angles with the measurements of tri-axial magnetic filed to obtain the yaw angle [17-19].The accelerometers not only measure gravity, but also sense the rigid body acceleration. Therefore, the measurement attitudes from the accelerometers are interfered with the accelerated flight states. Many researchers apply other methods to compensate the errors [20, 21].

In this study, the differential of velocity from GPS is utilized to compensate the measurement attitudes of phi and theta which obtained by measuring acceleration filed in the body frame,
where \( f_{ag}, f_{bg}, f_{dg} \) are from GPS in earth frame, \( f_{ab}, f_{db}, f_{db} \) represent output of the body acceleration, and \( f_{a}, f_{b}, f_{d} \) are compensated specific force, \( C^b_a \) represent attitude transformation matrix from earth to body frame which is defined by three rotations of Euler angles in Eq. (3)

\[
C^b_a = \begin{bmatrix}
\cos \theta \cos \phi & \cos \theta \sin \phi & -\sin \theta \\
-\sin \phi & \cos \phi & 0 \\
\sin \theta \cos \psi & \sin \theta \sin \psi & \cos \theta
\end{bmatrix}
\]

Then, the measurement attitudes of roll and pitch can be obtained as Eq. (4):

\[
\phi_a = \arctan \left( \frac{f_a}{\sqrt{f_a^2 + f_d^2}} \right) \\
\theta_a = -\arctan \left( \frac{-m_x \cos \phi_a + m_y \sin \phi_a}{m_x \sin \theta_a + m_y \cos \theta_a \cos \phi_a} \right)
\]

(4)

Therefore, the measured attitudes can be revised to use the measurement of the magnetic filed, and calculate the heading or yaw angle as [22]:

\[
yaw = \arctan \left( \frac{-m_x \cos \phi_a + m_y \sin \phi_a}{m_x \sin \theta_a + m_y \cos \theta_a \cos \phi_a} \right)
\]

(5)

where \( m_x, m_y, m_z \) are components of earth’s magnetic filed vector which measured by tri-axial magnetometer, respectively. 

**Quaternion-Based (Q-B) Process Model**

There are many methods used to determine the attitude of SUAVs, for example, Euler, Direction Cosine Matrix and Quaternion. Euler is the most straightforward way but with solution of the transcendental equation, and the Direction Cosine Matrix can directly obtain the attitude matrix but should solve nine equations with large computation, then the quaternion representation of the rigid body rotation generally has the least computation with only four variables. In order to propagate the attitude in time, the quaternion kinematics equation is given as:

\[
\begin{bmatrix}
\dot{q}_0 \\
\dot{q}_1 \\
\dot{q}_2 \\
\dot{q}_3
\end{bmatrix} = \begin{bmatrix}
0 & -p & -q & -r \\
-2q & 0 & p & -r \\
-2r & p & 0 & q \\
q & -r & -p & 0
\end{bmatrix} \begin{bmatrix}
q_0 \\
q_1 \\
q_2 \\
q_3
\end{bmatrix} \begin{bmatrix}
0 & p & -q & -r \\
-r & 0 & p & q \\
q & -r & 0 & p \\
r & -q & -p & 0
\end{bmatrix} \begin{bmatrix}
q_0 \\
q_1 \\
q_2 \\
q_3
\end{bmatrix}
\]

(6)

where \( q_0, q_1, q_2, q_3 \) are four components of the attitude quaternion, \( p, q, r \) are true angular rate of the body frame which can be derived by the following equation:

\[
\begin{bmatrix}
p \\
q \\
r
\end{bmatrix} = \begin{bmatrix}
w_x \\
w_y \\
w_z
\end{bmatrix} + \begin{bmatrix}
\eta_x \\
\eta_y \\
\eta_z
\end{bmatrix}
\]

(7)

where \( p, q, r \) are output of the tri-axial angular rate gyro, which contain real angular rate and the drifts of gyro. Substituting Eq. (1) and Eq. (7) into Eq. (6), the quaternion-based process model is given as:

\[
X = AX + IW
\]

(8)

we set the state vector \( X \) and the process noise vector as:

\[
X = [q_0 \ \ q_1 \ \ q_2 \ \ q_3 \ \ \epsilon_x \ \ \epsilon_y \ \ \epsilon_z \ \ \epsilon_{bx} \ \ \epsilon_{by} \ \ \epsilon_{bz}]^T
\]

(9)

\[
W = [w_x \ \ w_y \ \ w_z \ \ \eta_x \ \ \eta_y \ \ \eta_z]^T
\]

(10)

where \( \epsilon_x, \epsilon_y, \epsilon_z \) are first-order Markov process drift, and \( \epsilon_{bx}, \epsilon_{by}, \epsilon_{bz} \) are random constant, and \( w_x, w_y, w_z \) are process noise, \( \eta_x, \eta_y, \eta_z \) are driver noise of the rate gyro. So the process model express in terms of state equations is characterized as follows:
It is noted that Eq. (11) is a nonlinear model. However, the linear equation can be easy obtained by using partial derivatives of the states, and then the linear discretization model can achieve the filter propagation. It also can be seen that the quaternion is obtained naturally in the recurrent process rather than solved the quaternion by algorithms, such as first-order approximation or rotation vector et al. We have already received the measurement angle from the accelerometer and magnetometer in the last section. According to the relations between quaternion and Euler, the measurement quaternion vector as follows:

\[
Z = [q_{a0} \ q_{a1} \ q_{a2} \ q_{a3}]^T (12)
\]

where \( q_{a1}, q_{a2}, q_{a3}, q_{a4} \) are obtained as:

\[
\begin{align*}
q_{a0} &= \cos \frac{\phi}{2} \cos \frac{\theta}{2} \cos \frac{\psi}{2} + \sin \frac{\phi}{2} \sin \frac{\theta}{2} \sin \frac{\psi}{2} \\
q_{a1} &= \sin \frac{\phi}{2} \cos \frac{\theta}{2} \cos \frac{\psi}{2} - \cos \frac{\phi}{2} \sin \frac{\theta}{2} \sin \frac{\psi}{2} \\
q_{a2} &= \cos \frac{\phi}{2} \sin \frac{\theta}{2} \cos \frac{\psi}{2} + \sin \frac{\phi}{2} \cos \frac{\theta}{2} \sin \frac{\psi}{2} \\
q_{a3} &= \cos \frac{\phi}{2} \cos \frac{\theta}{2} \sin \frac{\psi}{2} - \sin \frac{\phi}{2} \sin \frac{\theta}{2} \cos \frac{\psi}{2}
\end{align*}
\]

(13)

Therefore, the output equation is a linear unit matrix as Eq. (14):

\[
Z = HX + V (14)
\]

where \( V \) is the measurement noise, and the output matrix \( H \) is:

\[
H = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 
\end{bmatrix}
\]

(15)

In a recursive cycle, the estimated quaternion is obtained, and the estimated attitude is gotten by using the following equation:

\[
\phi = \arctan \left( \frac{2(q_2 q_3 + q_0 q_4)}{q_0^2 - q_1^2 - q_2^2 + q_3^2} \right)
\]

\[
\theta = -\arcsin \left( 2q_1 q_2 - q_0 q_3 \right)
\]

\[
\psi = \arctan \left( \frac{2(q_2 q_3 + q_0 q_4)}{q_0^2 + q_1^2 - q_2^2 - q_3^2} \right)
\]

Angular Rate Integration (A-I) Process Model

The previous part has already expressed the one method which used for attitude determination. However, we also develop another algorithm, as a designing margin in our development scheme. The principle of the angular rate integration is straight from the relations between the angular rate and the angle [23]. The main purpose of the algorithm is to estimate the drift noise of the rate gyro accurately so as to compensate the integrated error effectively. In order to reduce the computation and the order of the Kalman filter, the drift features of rate gyro only consider the random constant and the white noise, the rate gyros error model as follows:

\[
\begin{align*}
p &= p_i + \varepsilon_{bs} + w_{gs} \\
q &= q_i + \varepsilon_{by} + w_{gy} \\
r &= r_i + \varepsilon_{bz} + w_{gy}
\end{align*}
\]

(17)

In each recursive process, the rate gyros drift can be estimated and subtracted from the rate gyro output, so the process model is developed in continuous domain as Eq. (18):

\[
\begin{align*}
\phi &= \phi_0 + \left( p - \varepsilon_{bs} - w_{gs} \right) dt \\
\theta &= \theta_0 + \left( q - \varepsilon_{by} - w_{gy} \right) dt \\
\psi &= \psi_0 + \left( r - \varepsilon_{bz} - w_{gy} \right) dt
\end{align*}
\]

(18)

Where, \( \phi_0, \theta_0, \psi_0 \) are initial attitudes, and \( dt \) is system sample time (0.01s). The discretized style of Eq. (18) is given as:

\[
X(k + 1) = \Phi \ X(k) + B \ U(k) + \Gamma \ W(k) (19)
\]

According to Eq. (19), the state vector \( X(k) \), the state transaction matrix \( \Phi \), the control matrix \( B \), the control input vector \( U(k) \), the noise matrix \( \Gamma \) and the process
The measurement attitude is also from the accelerometer and magnetometer, so the output matrix $H_k$ is given as:

$$
H_k = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0
\end{bmatrix}
$$

(22)

**AHRS Ground tests**

The ground test of the AHRS is divided into two parts to verify the accuracy and reliability of the attitude estimation system. The first one is under static state, which left the AHRS alone until the sensors reach a steady state. The second state is manipulated by external factors. It should be noted that the two sets of test data is derived from the one boot. As can be seen in Figure 1, the two Kalman filter algorithms have a good performance for estimating the Euler angles, the roll angle ranges within 0.6 degrees, and the pitch angle ranges within 0.3 degrees. The yaw angle with a higher noise level which lead to the yaw angle within 4 degrees range. The estimated drift feature of the rate gyro indicates that the random constant plays a main role in the sensor output. The detailed comparison results about the two methods list in Table 1.

It can be seen that the roll and pitch angles have a similar estimation accuracy, and the standard deviation of the yaw angle using A-I is a little bigger than Q-B algorithm.

**VELOCITY AND POSITION ESTIMATION**

The AHRS is usually considered as the inner loop of the SUAVs system. It can offer accurate attitude for the control system in real-time, and also provide the attitude information for the velocity and position.
estimation system. In this paper, we design a cascading AHRS filter with a separated SINS filter which is based primarily on the low-order structure and computational efficiency.

**Velocity Filter Designing**

In the velocity estimation system, the main measurement devices are accelerometer and GPS. The output signals of the accelerometer, which are the body frame acceleration in the process model, and the GPS could offer another way of getting the measured velocity.

The translational equations of motion are given by the relatively simple Eq. (23):

\[
\begin{align*}
\dot{u} &= -(wq - vp) + \frac{F_x}{m} \\
\dot{v} &= -(ur - wp) + \frac{F_y}{m} \\
\dot{w} &= -(vp - uq) + \frac{F_z}{m}
\end{align*}
\]  

(23)

where \( u, v \) and \( w \) are body velocities out the nose, \( m \) is the mass of SUAVs, \( F_x, F_y \) and \( F_z \) are translational forces acting on the SUAVs. This can be problematic because the accelerometer both senses the \( F/m \) term and the gravity component due to the attitude tilting. Hence the attitude must be available and accuracy from the preceding AHRS, and the earth’s gravity is filtered out from the direct measurement of the accelerometer. Then the measured model of the accelerometer can be given as:

\[
\begin{align*}
a_{ux} &= -\frac{F_x}{m} - g \sin \theta + \nabla r_x + w_{ax} \\
a_{uy} &= -\frac{F_y}{m} + g \cos \theta \sin \phi + \nabla r_y + w_{ay} \\
a_{uz} &= -\frac{F_z}{m} + g \cos \theta \cos \phi + \nabla r_z + w_{az}
\end{align*}
\]  

(24)

Treating the attitude estimated from the AHRS as input to the SINS, the process model of the velocity can be developed by substituting Eq. (24) to Eq. (23):

The measured velocity from GPS is in the earth frame, should convert to the body frame by utilizing attitude matrix \( C_b^c \), and the measured model express as follows:

\[
Z = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
u \\
w
\end{bmatrix}
+ \begin{bmatrix}
w_{vu} \\
w_{wm}
\end{bmatrix}
\]  

(26)

where \( Z \) is transformed velocity from GPS, and the measured noise of GPS is considered to be a typical Gauss process.

**Position Filter Designing**

According to the cascade process, the position estimation system is based on the velocity. In former section, the tri-axial velocity of the SUAVs has been determined in body frame. In order to consist with the GPS’s output, the body velocity should convert into the earth frame as follows:

\[
V_b^n = C^n_b V_b^c
\]  

(27)

where \( C_b^n \) is the transposed of attitude matrix, \( V_b^c = [u, v, w]^T \) is estimated velocity vector in the body frame, \( V_b^n = [v_n, v_w, v_id]^T \) is earth frame velocity vector. The general equation of motion for navigation in discrete domain can be presented as:

\[
S_{k+1} = S_k + V_{k+1} dt
\]  

(28)

The \( S_k = \begin{bmatrix} X_k & Y_k & Z_k \end{bmatrix}^T \) represents the three-dimensional positions in the earth frame, by expanding the Eq. (28) we can obtain:
\[
\begin{bmatrix}
X_{k+1} \\
Y_{k+1} \\
Z_{k+1}
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
X_k \\
Y_k \\
Z_k
\end{bmatrix} +
\begin{bmatrix}
dt & 0 & 0 \\
0 & dt & 0 \\
0 & 0 & dt
\end{bmatrix}
\begin{bmatrix}
V_{nw} \\
V_{ne} \\
V_{nd}
\end{bmatrix}
\]

(29)

\[X_k, Y_k, Z_k\] are Cartesian coordinate components which have to turn into the more commonly used geodetic-mapping coordinates of Latitude, Longitude and Altitude (LLA) for coinciding with the GPS output. As a consequence, the output model of the position is given as:

\[
\begin{bmatrix}
L \\
\lambda \\
h
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
L_{k+1} \\
\lambda_{k+1} \\
h_{k+1}
\end{bmatrix} +
\begin{bmatrix}
w_{pn} \\
w_{pe} \\
w_{pd}
\end{bmatrix}
\]

(30)

where \(L, \lambda, h\) are the GPS output, and \(w_{pn}, w_{pe}, w_{pd}\) are the measured noise.

VALIDATION BY FLIGHT TESTS

In this section, we present a serial of actual flight tests verify the performance and reliability of the developed avionics. In the following, the target small UAV is introduced, and then, the flight data is obtained by the onboard avionics.

Small Tilt-rotor Aircraft

The small tilt-rotor aircraft has a normal high-single-wing configuration with two nacelles rotorcraft systems fitted outside the wing. The horizontal, vertical tail with elevator and rudder are installed on the fuselage of the tail. Two engines are used to drive two sets of rotors through a synchronous shaft to ensure identical rotational speed of the rotors. A digital position control system and a worm gear and worm mechanism provides required moment for tilting the nacelles. There are 11 control servos to drive different aerodynamics interface. They have authority in the helicopter mode, conversion mode and the airplane mode. The aerodynamic configuration of the small tilt-rotor aircraft is shown in figure 3.

Flight Tests Data Analysis

The automatic helicopter mode in hovering flight is used to test the integrated GPS/SINS system. The results show in Figures 4-10 are obtained from the one automatic hover flight test. Figure 4 shows the character of the three-axis measured acceleration about the tilt-rotor, respectively. The X-axis and Y-axis have a similar vibrate level, and Z-axis has a great amplitude deviation. This indicated that the vibration of the vertical is very terrible.

Fig.3 The automatic hovering flight tests

Fig.4 The outputs of the triple axis accelerometer

Figure 5 represents the performance of the three-axis attitudes estimation in degrees, respectively. As can be seen that the maximum deflection is approximately 8° in roll, and the mean value is about 2.66°. This indicates that in the trim flight states, the tilt-rotor has a right constant deviation in roll. The pitch angle is approximately arrange from -5° to 5° during the hover flight, which indicates that the tilt-rotor in a
horizon level.

Fig.5 Euler angles estimation

Fig.6 Velocities estimation

Figure 6 represents three-axis velocity output from the SINS, and figures 7-8 represent relations between the attitudes and the velocities, respectively. As for convenient contrast, the amplitude of the velocities are augmented coincide with the attitudes. It is noticeable that the roll and lateral velocity, pitch and longitudinal velocity are related well.

Fig.7 roll angle Vs lateral velocity

Fig.8 pitch angle Vs longitudinal velocity

Fig.9 GPS Vs estimated position of North

Fig.10 GPS Vs estimated position of East

Figures 9-10 demonstrates effectiveness of the north and east position estimation, it is obviously that the position of the filtered data is smoother than the original GPS greatly. It is very useful for the control system with those soft commands.

CONCLUSIONS

In this work, a completed set of navigation algorithm is developed for the small tilt-rotor aircraft, the hardware of the onboard navigation system is designed and has been successfully implemented. A series of actual
flight tests are conducted and the following conclusions can be given:

(1) Considered the margin design, the two attitude estimation algorithms are developed and implemented in the navigation computer in the meantime. The flight test indicates that Kalman filter estimates the attitude property, and the angular rate integration algorithm with a simple and efficient structure is suitable for low-power processor navigation system.

(2) The algorithms of the attitude, velocity and position are designed by adopting the cascaded approach. The order of the Kalman filter is reduced effective and the computation is saved.

(3) The algorithms are operated in real-time, and the reliability of the overall tilt-rotor system is also verified by flight tests.

REFERENCES


