Computers and Electronics in Agriculture 134 (2017) 19–26

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Attitude measure system based on extended Kalman filter for multi-rotors

Zhang Tiemin *, Liao Yihua

Key Laboratory of Key Technology on Agricultural Machine and Equipment, Ministry of Education, South China Agricultural University, Guangzhou 510642, China

ARTICLE INFO

Article history:
Received 24 March 2016
Received in revised form 23 October 2016
Accepted 26 December 2016
Available online 19 January 2017

Keywords:
Multi-rotor
Attitude measure
Sensor fusion
Extended Kalman filter
Quaternion

ABSTRACT

Attitude measure is the basis of multi-rotors flight control. An attitude measure system was constructed based on MEMS gyroscope, accelerometer and magnetometer to realize three-axis attitude measure of multi-rotors. The system included STM32F103 as controller, integrated accelerometer and gyroscope MPU6050, magnetometer HMC5883 as measure sensors. A sensor fusion quaternion-based extended Kalman filter compliant with this system was proposed. The attitude quaternion and the gyroscope bias were introduced as state vector, the acceleration and the magnetic measured by accelerometer and magnetometer were introduced as observation vector. Extended Kalman filter combined the nice performance of gyroscope in dynamic with accelerometer and magnetometer in static. The optimized covariance value combination can improve the accuracy of attitude estimation and had excellent tracking performance in dynamic. The measure system based on extended Kalman filter was testified and analyzed by static and dynamic tests. Experiment results illustrated that the system can obtain the information of each sensor. The attitude measure system based on extended Kalman filter realized precision attitude measure for multi-rotors in dynamic circumstances. It may lay foundation for UAV remote control.

0. Introduction

Multi-rotors is being introduced into almost every aspect of life. Agriculture is one such domain where multi-rotors is successfully used to reap numerous benefit. Croplands are extensive, with a size of up to several kilometers. Hence, it is necessary to use multi-rotors to hover and acquire accurate real-time target image to detect water accumulation on plant surface (Lee et al., 2010). Another key point is that it can work on farmland. For example, if a disease is detected, insecticides can be used to against them. Multi-rotors can transport these substances and release them at a particular point when necessary. Aerial remote sensing with high-resolution imaging showed a great potential for detecting disease-infected trees, evaluating the emergence and spring stand of wheat (Sankaran et al., 2015, 2010; Garcia-Ruiz et al., 2013).

Multi-rotors, which usually has more than two rotor propellers, has the advantages of taking off and landing vertically, simple structure, high mobility, good safety and easy maintenance. It is an understable and strong coupling system with 6 freedoms and 4 inputs. Therefore, to improve the vehicle's stability and controllability to make it fly autonomously or be guided manually is very useful. Attitude measure is an important part of the control system in multi-rotors and the accuracy of the measure system impacts control performance significantly. As a result, an attitude measure system needs to be constructed for the multi-rotors. Moreover, it can provide attitude information for UAV remote control operation test system of Zhang et al. (2015).

MEMS (Micro-Electro-Mechanical System) technologies have rapid developed during recent years. It is the high tech electronic mechanical devices that incorporate the technology of lithography, etching, silicon micro process, non silicon micro process and precision mechanics. Pastell et al. (2008) introduced a system, which was composed of electromechanical film, can detect dynamic forces to identify cow's lameness. In addition, the system suitable for attitude measure in multi-rotors has limitations on size, weight and power consumption (Liu et al., 2012; Wu and Yan, 2012). In order to achieve precision measurement, a sensor-integrated algorithm which could process data fusion and be compliant with the proposed hardware system should be researched in this study.

Different fusion algorithms such as Kalman filter, complementary filter, gradient descent method have been implemented in sensor-integrated systems these years. The gradient descent algorithm was provided in literature of Peng et al. (2015). Liao et al. (2014) had developed a multi-sensor data fusion method with fuzzy-PI deviation correction based on quaternion attitude system.

* Corresponding author.
E-mail address: tiemin_zhang@sina.com (T. Zhang).

http://dx.doi.org/10.1016/j.compag.2016.12.021
0168-1699/

While there are multiple fusion algorithms, Kalman fusion algorithm has been extensively implemented. Kalman filter is a recursive algorithm for efficient estimation of the process subjected to random disturbance based on minimum variance estimation (Xie et al., 2007).

In order to increase the attitude measuring precision, Yang et al. (2012) introduced an extended Kalman Filter (EKF) to integrate attitude data from different sources, however, only simulation results were given. Extended Kalman filter methods for attitude estimation were analyzed in literature of Huang et al. (2005). Gauss-Newton iterative method was employed to calculate the accelerometer and magnetometer vectors as measurement vector. Measure data collected from the sensors were used to test the filter. In the research carried out by Xue et al. (2009), a new quaternion-based extended Kalman filter algorithm by using the modified Gauss-Newton algorithm was introduced to improve the accuracy of attitude estimation. The Kalman filter of Nie et al. (2013) embedded with the gradient descent method was proposed to work out the sensors fusion by using measure information from gyroscope, accelerometer and magnetometer.

Kalman filter adopts recursive algorithm and needs small storage. It not only can be applied in a stationary stochastic process, but also a multi-dimensional and non-stationary random process (Fu et al., 2003). However, few researchers have addressed the problem of realization of attitude system based on extended Kalman filter and illustrated covariance matrices value used in the filter. Therefore, the aim of this work is to create a flight attitude measurement system based on STM32F103 controller, MEMS inertial sensors MPU6050 and HMC5883L. Because the cost of STM32F103, MPU6050 and HMC5883 were \$2.1, \$5.5 and \$1.7 respectively, a low-cost attitude measure system by integrated MEMS sensors to provide accurate attitude measure for UAV became available. The information from gyroscope, accelerometer and magnetometer were integrated by Kalman filter. Extended Kalman filter was adopted because the state matrix and the observation matrix of the system in this paper were nonlinear (Huang and Wang, 2015). In the filter, the quaternion state vector was built from gyroscope and its deviations were corrected by gravity field and magnetic field to estimate the attitude of multi-rotors.

The remainder of this paper is organized as follows. The definition of coordinates and the mathematical basis of the quaternion and its conversions are presented in Section 1. Section 2 is dedicated to the mathematical formulation of extended Kalman filter identification approach and its utilization in the measure system. The experimental setups in this research are described in Section 3. The results of covariance matrices value combinations in this system and the static and dynamic performance based on these combinations are also presented in this section. At the end of Section 4, the discussions and conclusions of this research are presented.

1. Coordinate and quaternion matrix definition

As indicated in Fig. 1, the navigation coordinate system n applied in this paper is North-East coordinate. The body coordinate system b is fixed to the origin of multi-rotors, Ox_b points to the front, Oy_b points to the right while Oz_b points to below. The pitch angle θ of aircraft is between Ox_b axis and ground level, the roll angle φ is between Oz_b axis and the vertical plane Ox_b axis lies in, the heading angle ψ is between the Ox_b axis of aircraft and the North.

Euler angle, direction cosine and quaternion have been the definition methods of orientation in attitude measure system by far. In attitude estimate, the measure vectors from body coordinate can be converted to navigation coordinate by coordinate conversion matrix C_b^n. In Euler angle, the representation of conversion matrix C_b^n is defined by

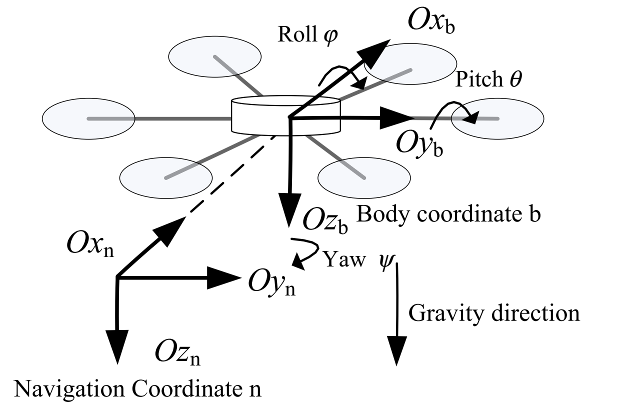

Fig. 1. Navigation coordinate and body coordinate of multi-rotors.

$$C_b^n = \begin{pmatrix} \cos\varphi\cos\psi + \sin\varphi\sin\theta\sin\psi & \cos\theta\sin\psi & \sin\varphi\cos\psi - \cos\varphi\sin\theta\sin\psi \\ -\cos\varphi\sin\psi + \sin\varphi\sin\theta\cos\psi & \cos\theta\cos\psi & -\sin\varphi\sin\psi - \cos\varphi\sin\theta\cos\psi \\ -\sin\varphi\cos\theta & \sin\theta & \cos\varphi\cos\theta \end{pmatrix}. \tag{1}$$

Attitude estimation resolved by quaternion can reduce computation and avoid singularity problem of Euler angle. The expression of quaternion is $\boldsymbol{q} = [q_0\ q_1\ q_2\ q_3]^{\mathrm{T}}$. In quaternion, body coordinate can be achieved by continuous rotation conversions of navigation coordinate without interruption. Inverse matrix of conversion matrix is the transposition of itself. Quaternion coordinate conversion matrix from navigation coordinate to body coordinate is,

$$C_n^b(\vec{q}) = \begin{bmatrix} q_0^2+q_1^2-q_2^2-q_3^2 & 2(q_1q_2+q_0q_3) & 2(q_1q_3-q_0q_2) \\ 2(q_1q_2-q_0q_3) & q_0^2-q_1^2+q_2^2-q_3^2 & 2(q_2q_3+q_0q_1) \\ 2(q_1q_3+q_0q_2) & 2(q_2q_3-q_0q_1) & q_0^2-q_1^2-q_2^2+q_3^2 \end{bmatrix}. \tag{2}$$

Combining Eqs. (1) and (2) yields attitude angle as follows,

$$\begin{cases} \theta = \arcsin\left((C_n^b(\vec{q}))_{23}\right), \left[\frac{\pi}{2}, \frac{\pi}{2}\right] \\ \phi = -\arctan\left(\frac{(C_n^b(\vec{q}))_{13}}{(C_n^b(\vec{q}))_{33}}\right), [-\pi, \pi]. \\ \psi = \arctan\left(\frac{(C_n^b(\vec{q}))_{21}}{(C_n^b(\vec{q}))_{22}}\right), [-\pi, \pi] \end{cases} \tag{3}$$

In strap-down inertial navigation system, the relationship between angular velocity and unit quaternion is as follow,

$$\begin{bmatrix} \dot{q}_0 \\ \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} = \frac{1}{2}\begin{bmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & \omega_z & -\omega_y \\ \omega_y & -\omega_z & 0 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 0 \end{bmatrix}\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix}, \tag{4}$$

where ω_x, ω_y, ω_z are the real rotation rates around x, y, z axis in the body coordinate measured by gyroscope (Qin et al., 1998).

2. Attitude estimation in Kalman filter

2.1. Kalman filter

MEMS gyroscope has very fast dynamic response and great accuracy except for errors which composes drift bias and white noise. The raw data from gyroscope cannot be used directly, because it infiltrates drift bias over time. In addition, it does not provide an absolute angle since the angle information from gyroscope is a relative angle from the initial point. The accelerometer has high accuracy in static. But it is influenced by acceleration motion and cannot restrain high dynamic maneuvers. Magnetome-