Quad-Copter Posture Control Using Fusion Filter of Complementary Filter and Kalman Filter Using MEMS Sensor

Min-Seok Jie¹, Seung-Hun Kim² and Won-Hyuck Choi^{3*}

 ^{1,3}Department of Avionics Engineering Hanseo University
236-49, Gomseom-ro, Nam-myeon, Taean-gun, 32158 Chungcheongnam-do, Republic of Korea
²Department of Aeronautical Systems Engineering Hanseo University
236-49, Gomseom-ro, Nam-myeon, Taean-gun, 32158 Chungcheongnam-do, Republic of Korea
{³choiwh, ¹jiems}@hanseo.ac.kr, ²kimsh753@naver.com

Abstract

On this paper, we used a separate MEMS sensor on the quad-copter to perceive and maintain the posture from the vibration the quad-copter received. We propose a stable posture adjustment method by merging the complementary filter and the Kalman filter. The safety improvement of the attitude control was verified by simulation and actual quad helicopter. MALTAB simulation results were compared using Kalman filters and complementary filters for gyro data and acceleration data received from MEMS sensors. In this study, we investigated the stability analysis of the flight posture using the MEMS sensor equipped with the equipment and the quad pilot. Based on the data output of the convergence type complementary filter and the Kalman filter, it is attached to the real quad to control the motor speed and verify the stability control performance.

Keywords: We would like to encourage you to list your keywords in this section

1. Introduction

Many studies have been conducted at home and abroad on filters to reduce noise and errors by using MEMS sensors. In 2016, using low cost MEMS sensors, we developed our own design Nano-inertial measuring unit (nIMU) to determine the position and direction of multirotor ROCs from the output. Use the Gauss-newton method to provide calculated Quaternion inputs for Kalman filters that reduce the dimension of the state vector and linearization of the measurement equation. It was also used to preprocessing MEMS sensor measurements to demonstrate accuracy of direction estimation and improvement in real-time performance based on simulation and experimental verification[3].

And in the same year, the original data from low cost MEMS published a study to validate simulations to minimize the impact of abnormal values on environmental conditions and to estimate bias effectively. As such, many design studies are conducted on filters for a number of errors and stability using MEMS sensors. The purpose of this study is to use MEMS sensors to receive data from the gyro sensor and acceleration sensor to obtain results from a fused tabling filter and Kalman filter. Apply the data from the fusion filter to the quad to compare the stability and reliability of the posture control [1, 2].

Received (April 15, 2018), Review Result (July 5, 2018), Accepted (July 10, 2018) * Corresponding Author

2. MEMS Inertia Sensor

As explained by the appointed sensors in MEMS, the fundamental noise is generated by the impact of the air molecules on the thermal vibration that vibration the ultra-small sensor. Noise due to these factors results in zero variation, drift, bias error, *etc.*, and a large cumulative error in the process of integrating to produce a slope rejection.

The data measured by the gyro sensor is output with the data printed, such as noise and bias error, for this reason, errors accumulate and can't be used in practice.

The acceleration sensor has a wide range of errors, which leads to less accurate position information. For this reason, sensors are fused to reduce noise and bias errors in low-cost sensors. First, because the accumulated error of gyro sensor is large, it eliminates the accumulated error by compensating. Then, the compensated gyro sensor and acceleration sensor data are used to estimate the Roll, Pitch of the quadcopter.



Figure 1. Angle Detection Principle of Acceleration Sensor

An acceleration sensor is a sensor that measures the movement over a period of time and produces a charge proportional to the magnitude of the action when the action occurs. It also outputs data in the direction of gravity acceleration without the force being applied and continuously outputs a value of 1 g around the Z-axis in horizontal conditions. The detected acceleration converts the electrical signal relative to its size and is processed with information indicating its movement in a particular direction.

The acceleration sensor used in this study is a three-axis sensor that compensates for posture and outputs analog output of changes in acceleration of the X, Y and Z axes. Units of acceleration are expressed in gravity acceleration g and data on acceleration can be presented using the tilted angle as shown in Figure 1.

The output value of the acceleration sensor Y axis for the X-axis and the output of the Z axis is a_z .

In the same way ϕ_c is also as shown in Equation (1) and Equation (2) by the axis slope X_c .

$$\theta_{\rm c} = \tan^{-1} \left(\frac{a_{yc}}{a_{zc}} \right) \tag{1}$$

$$\phi_c = \tan^{-1} \left(\frac{a_{xc}}{a_{zc}} \right) \tag{2}$$

The X-axis acceleration output of the acceleration sensor is indicated by. The acceleration sensor is sensitive to external forces, such as impact and vibration, which makes it difficult to extract the actual slope information and cannot measure the slope value with the acceleration sensor alone in an unstopped state of motion. However, the numerical representation of static gravitational acceleration can be used to show absolute slope.

Gyro sensors measure angular speed unlike acceleration sensors, and gyro sensors that are chip-type with MEMS technology also measure angular speed of gas. With sensors measuring the acceleration of each axis on a rotating object, it is possible to measure the angular velocity of an object by detecting the rotational velocity from the outside, and to measure the angular velocity of the object by integral of the axis 3.

However, as the angle is estimated during integration, the cumulative error becomes greater because the error of drift and bias are printed together and accurate data and posture information will not be available.

3. Fusion Filter

3.1. Complementary Filter

The gyro sensor has an integral error during the integration process to obtain the rotation angle, and as the number of cycles is increased, the errors accumulate, resulting in a drift of the rotation. In addition, the acceleration sensor also has its own acceleration characteristics, resulting in an error in values for fast rotation and rapid change of direction.

For this reason, it is a method to mix the faults of the gyro sensor and the acceleration sensor using the High Pass Filter + Low Pass Filter.

Because the gyro sensor in low cost MEMS is sensitive to changes in angle, the drift phenomenon is greatly affected by the high pass filter, and the error measured by the acceleration sensor is sensitive to the external force of the sensor [4].

$$\phi = \frac{as}{as+1} \left(\frac{1}{s} \dot{\phi}_g\right) + \frac{1}{as+1} \phi_a \tag{3}$$

The value for removing the error bias of the gyro sensor value from Equation 2 ϕ_g and the angle measured from the acceleration sensor was expressed as ϕ_a . Form 3 can be expressed in the form shown below in 4.

$$\phi = \frac{1}{s} \left(\dot{\phi}_g + \frac{1}{a} (\phi_a - \phi) \right) \tag{4}$$

Figure 2 below shows the concept of a detailed filter and the expression 3.18 in block order is shown in Figure 3.



Figure 2. Complementary Filter Configuration

International Journal of Control and Automation Vol. 11, No. 8 (2018)



Figure 3. Magnetic Resonance Sensor Block

The angle ϕ_g measured by the gyro sensor in the block degree is integrated into the ϕ , and the angle measured by the acceleration sensor ϕ_a multiplied by 1a ϕ . This method of integration is different.

3.2. Kalman Filter Algorithm

Kalman filters are used to repeatedly estimate estimates that minimize errors from inaccurate measurements, to detect or remove desired signals from noisy signals, and to use the system model[12].

These Kalman filters are used to predict change in the position of quadcopters, and they vary in weight over time, unlike other filters. Kalman Filter is a long-term mathematical filter algorithm that efficiently performs real-time processing of signals with excellent noise rejection and has high prediction accuracy. However, the common Kalman filters have good performance, but the downside is that they can only be used if the system model is unclear and the measurements are mixed with white noise. Although the algorithm for the Kalman filter consists of four steps, the larger range can be seen as two phases, the prediction, and estimation process.



Figure 4. Kalman Filter Algorithm

The Kalman filter algorithm is a technique for estimating the state variables of a target system using probabilistic models in a linear system that contains noise and measurements from predictable targets.

Thus, the performance of the target system depends significantly on the degree to which the mathematical modelling is like the actual system, such as expression 5 and 6, to apply the Kalman filter.

$$x_{k+1} = Ax_k + w_k \tag{5}$$

$$z_k = H x_k + v_k \tag{6}$$

Where X_k is the status variable, Z_k is the measurement value, and A is the pre-state matrix for how the system behaves over time, and H is the measurement variable. And W_k is the noise introduced into the system that affects the state variable V_k , which is the measured noise for the sensor. The Kalman filter has the following algorithm as shown in Figure 4.

4. Position Control using a Complementary Filter and a Kalman Filter

From Chapter 4, the results simulated by MATLAB were applied directly to the quadcopter. The following graphs were processed by receiving data directly from the ATmega 2560 board on the quadcopter with a detailed filter and a Kalman filter.

Figure 5 shows a graph of unfiltered data and detailed filters.



Figure 5. Basic Data and Complementary Filter Data Graph

The graph in Figure 6 compares the values applied to the Kalman filter with data coming directly from the quad. Common values are often associated with vibration and noise, which results in high values. However, the graph with the Kalman filter found that the noise section had a stable output.



Figure 6. Basic Data and Kalman Filter Data Graph

The graph in Figure 7 compares the data coming from a quad-copter with a complementary filter and a Kalman filter. The filter of the tablecloth is not released, but there is a high error value. Only the Kalman filter is released and contains the overshoot, but it has been verified that the given angle is reached normally.



Figure 7. Comparison of Complementary and Kalman Filter in Quad Copter

Figure 8 shows the response status of data coming from Quad-copters, giving a constant slope to the tableware and Kalman filters. The Kalman filter is a filter that predicts the value over time to remove noise and thus follows some noise, but it can be found to be close to the value when given 30 degrees. The detailed filter passes through the High Pass Filter (HPF), and the acceleration sensor passes through the Low Pass Filter (LPF) filter, so it was confirmed that the value is not emitted.



Figure 8. Complementary Filter and Kalman Filter Response Characteristics in Quad Copter

Figure 9 shows that when the data coming from the quadcopter are compared to the graph applied through the filter fusion, the filter is fused from the Kalman filter.



Figure 9. Kalman Filter and Fusion Filter Graph in Quad Copter

Below Figure 10 has found that the results of experiments with the Kalman filter and the fusion filter in the Quad-copter are more stable at the response characteristics of the output than in the Kalman filter.



Figure 10. Comparison of Kalman Filter and Fusion Sensor Response Characteristics in Quad Copter

5. Conclusion

To control the position of the quadcopter, the measured position information using the gyro sensor and acceleration sensor was used to integrate into the detailed filter and then proceed through the Kalman filter. If only one filter is applied, there is a value of the error, though low emission is present. On the other hand, it was found that the stability of the Kalman filter would take some time to stabilize, but that the value would be more accurate than that of the detailed filter. When the tableware filter and the Kalman filter were combined, the tableware filter decreased the computation for the angle, and the Kalman filter reduced the time it reached to estimate the reduced value. Using this proven filter fusion, programming to control the speed of the motor has been implemented and it can be found that the two filters are more helpful in position control than in using each other.

In this study, we finally tested the posture control simulation using a compartment filter, a Kalman filter, a fusion filter and applied the fusion filter to the actual quadcopter.

References

- X. Zhang, Z. Yang, T. Zhang and Y. Shen, "An improved Kalman filter for attitude determination of multi-rotor UAVs based on low-cost MEMS sensors", In Guidance, Navigation and Control Conference (CGNCC), IEEE Chinese, (2016), pp. 407-412.
- [2] H. G. Min, "Design of Complementary Filter using MEMS-type Gyroscope and Accelerometer", Changwon University, (2011).
- [3] W. S. Jo, "A Study of a Calibration method and Flight Test for MEMS Sensor", Korea Aviation University, (2017).
- [4] D. H. Cho, "Design and control of a quad-rotor UAV", KAIST, (2009).
- [5] Y. H. Ok, "Implementation on the Attitude Controller of the Quad-rotor using DSP", Hoseo University (2015).
- [6] S. T. Pham and M. T. Chew, "Sensor signal filtering in quadrotor control", In Sensors Applications Symposium, (2014), pp. 293-298.

- [7] H. S. Kim, "A Design of Hovering System for Quadrotor UAV using Multi-Sensor Fusion", Seo-kyeong University, (2016).
- [8] J. S. Kim, "The Simulator for Control of Quad copter using sensor combination", Dong-A University, (2012).
- [9] S. Y. Hwang, J. H. Park and J. M. Lee, "Detection of Inclination for Quadcopter's Landing Position Control", Institute of Control, Robotics and Systems, (2010), pp. 35-38.
- [10] Y. J. You and J. R. Ryoo, "Geomagnetic Sensor Compensation and Sensor Fusion for Quadrotor Heading Direction Control", Journal of The Institute of Electronics and Information Engineers, vol. 53, no. 7, (2016), pp. 95-102.
- [11] S. K. Han, I. H. Lee and N. R. Park, "Reliability of static balance abilities measure using a smartphone's acceleration sensor", Journal of the Korea Academia-Industrial Cooperation Society, vol. 17, no. 6, (2016), pp. 233-238.
- [12] M. D. S. Rahman, C. H. Choi, S. K. Kim, I. D. Park and Y. P. Kim, "Noise-robust electrocardiogram Rpeak detection with adaptive filter and variable threshold", Journal of the Korea Academia-Industrial Cooperation Society., vol. 18, no. 12, (2017), pp. 126-134.
- [13] K. S. Ryu, B. K. Kim, D. J. Kim, M. S. Jang, H. S. Ko and H. C. Kim, "A State-of-Charge estimation using extended Kalman filter for battery of electric vehicle", Journal of the Korea Academia-Industrial Cooperation Society., vol. 18, no. 10, (2017), pp. 15-23.

Authors



Seung-Hun Kim, he is a master's degree in Aeronautical System Engineering, Hanseo University. He graduated from the Department of Aeronautical and Mechanical Engineering, Hanseo University. He is studying Kalman filters, embedded systems, and smart network communications.



Min-Seok Jie, he graduated from the Ph.d degree in the department of avionics Engineering from Korea Aerospace University in 2006. he is Hanseo University Avionics Engineering Professor in to the present in 2008.



Won-Hyuck Choi (**Corresponding author**), he received the Ph.D. degree in avionics from Korea Aerospace University, Korea. He was a Professor of smart network at Doowon Technical University College, Korea. urrently, he is Professor of avionics at Hanseo University, Korea, where he has been since 2014. His present research interests include embedded system, home network.

International Journal of Control and Automation Vol. 11, No. 8 (2018)