

## COMPLEMENTARY FILTER FOR UAV ATTITUDE ESTIMATION

**Annotation.** This paper considers filtering techniques, used for unmanned aerial vehicles attitude estimation, a critical aspect of navigation and autonomy. The study compares traditional Kalman Filters with complementary filters, which use sensor fusion to adjust the measurements. The complementary filter structure, main equations, and principles are given in this paper.

**Key words:** inertial measurement unit (IMU), complementary filter, data processing, attitude estimation, autonomous navigation.

## INTRODUCTION

Unmanned aerial vehicles (UAVs) are becoming more autonomous as their tasks grow in complexity. A fundamental capability required to enable drones to operate without human involvement is UAV attitude estimation. It needs frequent and accurate data from sensors, that could be used for defining the drone's position and orientation (pose) [1].

Technologies, that are used for the defined task vary depending on the features of the environment, in which the drone is supposed to operate [2]. All UAVs are equipped with inertial measurement units (IMUs), which provide data at frequencies of up to 100 Hz, enabling them to function independently of external information sources for short periods of time. Based on the fact, that IMU has a continuously growing bias, measurements must be corrected with additional sources [3].

For outdoor operations, the GPS is widely used to complement IMU data. For a GPS-denied environment, visual-inertial odometry (VIO) is a common approach for pose estimation.

Although the mentioned technologies provide accurate data, their update rate is slower than that of IMUs. That is why, besides sensor fusion, filtering algorithms are essential for IMUs to reduce bias and noise. Moreover, such filters allow IMU to be used independently from other sensors for short-time tasks, particularly in small-size drones.

## LITERATURE OVERVIEW

One of most widely used techniques for filtering the measurements from IMU is using the Kalman Filter (KF). This method is based on the principle of comparing previous values with current measurements, which prevents getting random values and getting rid of noise. As for now, Extended KF [4, 5] and Unscented KF [6] are greatly developed.

However, KF is mostly used to correct data from one source of information, which results in continuously growing errors. That is why data for drone attitude estimation is obtained from different sensors or both sensor and mathematical models of UAVs [6].

Sensor fusion is implemented in complementary filters, which are used both with KF and as an alternative. Increasing the accuracy of IMU measurements could be done by using nonlinear complementary filters, such as direct, passive, and explicit complementary filters [7].

## RESULTS

UAV pose could be represented in various forms. The most popular of them are Euler angles, rotation matrices, and quaternions. Commonly, all of them are used for low-level UAV control, that is converting the desired position to the angular velocity or voltage for motors.

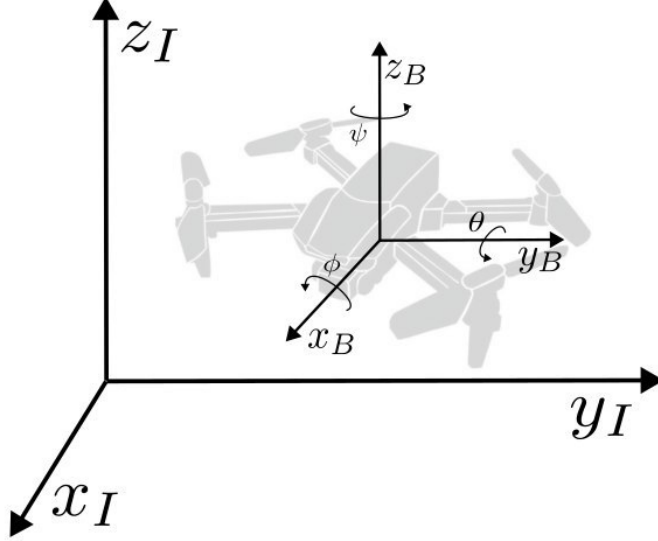


Figure 1. Euler angles representation

In this paper we will use Euler angles representation. Euler angles are roll  $\phi$ , pitch  $\theta$  and yaw  $\psi$  or the tilt of body-attached frame  $B$  above  $x$ ,  $y$ , and  $z$  respectively in an inertial frame  $I$  (commonly fixed on the ground). The frames and Euler angles are illustrated in Figure 1.

Modern IMU consists of 3 sensors: accelerometer, gyroscope, and magnetometer. The values different sensors are compared to get the filtered measurement. For this process,

complementary filters are used.

For further calculations, we assume that angular velocities  $\omega_x, \omega_y, \omega_z$  are the Euler angles derivative:

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \quad (1)$$

For and roll and pitch angles estimation measurements from accelerometer and gyroscope are used. The scheme for pitch correction, done by complementary filter, is represented in Figure 2.

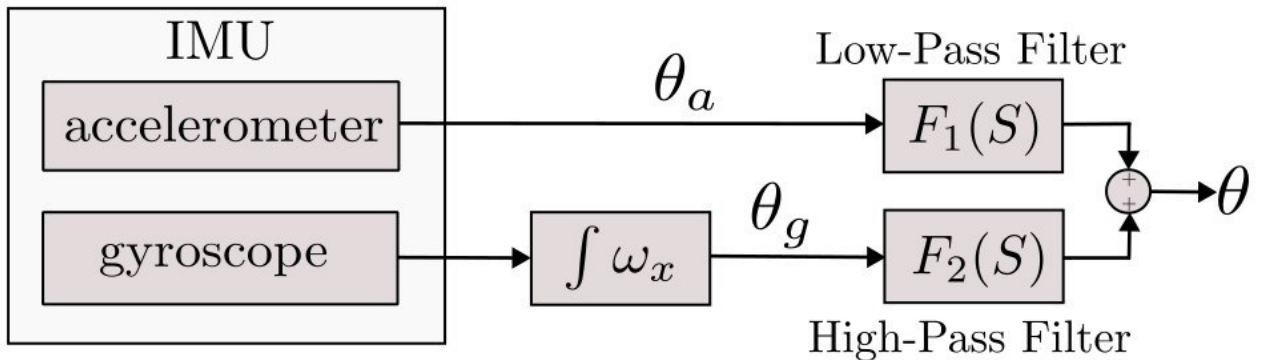


Figure 2. Complementary filter

A low-pass filter  $F_1(s)$  is used to reduce noise in measurements from an accelerometer and a high-pass  $F_2(s)$  filter helps to get rid of gyroscope bias, what is

the result of time-dependable drift of measurement. Adding filters together we have to obtain:

$$F_1(s) + F_2(s) = 1 \quad (2)$$

The Laplace transform of the filters are designed as follows:

$$F_1(s) = \frac{\tau}{\tau s + 1} \quad (3)$$

$$F_2(s) = \frac{s}{\tau s + 1} \quad (4)$$

where  $\tau$  is the time constant, which defines cutoff frequency and relative weights to used measurements. It is adjusted during flight testing. Generally, the weight of values got from gyroscope is greater than 95%, so that the weight of accelerometer data is lower than 5%.

The resulting equation for pitch is:

$$\theta(s) = \frac{\tau}{\tau s + 1} \cdot \theta_a(s) + \frac{s}{\tau s + 1} \int \omega_y(s) ds \quad (5)$$

Filtering of roll measurements are analogically described.

Yaw estimation requires fusion of data from magnetometer and gyroscope. To obtain the angle for yaw from magnetometer, its measurements have to be projected on horizontal plane:

$$m_x^I = \widetilde{m}_x^B \cos \theta + \widetilde{m}_y^B \sin \phi \sin \theta + \widetilde{m}_z^B \cos \phi \sin \theta \quad (6)$$

$$m_y^I = \widetilde{m}_y^B \cos \theta + \widetilde{m}_z^B \sin \phi \quad (7)$$

where  $m_x^I, m_y^I$  are magnetometer measurements calculated for inertial frame, and  $m_x^B, m_y^B, m_z^B$  are magnetometer measurements in body-attached frame.

The yaw value from magnetometer data could be found as follows:

$$\psi_m = \arctan2(m_x^I, m_y^I) \quad (8)$$

Considering the given algorithm, yaw estimation process has several issues, such that:

- Using magnetometer measurements, the difference in geographic location between true and magnetic North must be considered, as in the majority of cases trajectory for the flight is created with respect to true North;
- Magnetometer measurements might be influenced by magnetic interference from onboard electronics and external sources;
- Inaccuracies in pitch and roll angles estimation influence the yaw estimation, as they are used for magnetic vector projection on inertial frame.

Equation, that describes the yaw filtering by fusing measurements from gyroscope and magnetometer, is designed as follows:

$$\psi(s) = \frac{\tau}{\tau s + 1} \cdot \psi_m(s) + \frac{s}{\tau s + 1} \int \omega_z(s) ds \quad (9)$$

## CONCLUSIONS

The described complementary filter is simple in implementation and requires minimal computational resources, making it highly suitable for small UAVs. It combines measurements from accelerometer, gyroscope and magnetometer to get precise values for drone orientation. Its effectiveness in GPS-denied environments broadens the capabilities of IMU usage, making it possible to be the only source for pose estimation, particularly for mini-UAVs. The complementary filter serves as a robust foundation for advancing UAV autonomy.

Our future work will focus on implementing the described filter on a physical mini-UAV. This will include quantitative assessments of accuracy, and stability.

## REFERENCES

- [1] Муравйов О. В. Перспективи розвитку технологій та підвищення рівня автономності БПЛА / О.В. Муравйов, І.О. Довбиш, Р.М. Галаган, Г.А. Богдан, А.С. Момот // *Вчені записки ТНУ імені В.І. Вернадського. Серія: технічні науки*. – 2023. – Том. 34 (73). – № 2. – С. 199-205.
- [2] Довбиш І. О. Силові установки та джерела енергії сучасних БПЛА / І.О. Довбиш, О.В. Муравйов, Р.М. Галаган, Г.А. Богдан, А.С. Момот // *Вчені записки ТНУ імені В.І. Вернадського. Серія: технічні науки*. – 2023. – Том. 34 (73). – № 5. – С. 16-21.
- [3] Довбиш І.О., Муравйов О.В. Залежність архітектури рою від рівня автономності БПЛА. *XVI Всеукраїнська науково-практична конференція студентів, аспірантів та молодих вчених «Погляд у майбутнє приладобудування»*, м. Київ, збірник праць конференції. – 2023. – С. 158-161.
- [4] Mao, Guoqiang & Drake, Samuel & Anderson, Brian. Design of an Extended Kalman Filter for UAV Localization. *Conference Proceedings of 2007 Information, Decision and Control, IDC*. – 2007. – pp. 224-229.
- [5] Tayebi, Abdelhamid & Roberts, Andrew & Benallegue, Abdelaziz. Inertial measurements Based dynamic attitude estimation and velocity-free attitude stabilization. *American Control Conference*, San Francisco, USA – 2011. – pp. 1027-1032.
- [6] Goslinski, Jaroslaw & Giernacki, Wojciech & Królikowski, Andrzej. A Nonlinear Filter for Efficient Attitude Estimation of Unmanned Aerial Vehicle (UAV). *Journal of Intelligent & Robotic Systems*. – 2019. – 95(6). – pp. 1079-1095.
- [7] Jean-Michael Pflimlin Robert Mahony, Tarek Hamel. Nonlinear Complementary Filters on the Special Orthogonal Group. *IEEE Transactions on Automatic Control*. – 2008. – 53(5). – pp. 1203-1218.

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