Three-dimensional attitude determination using vector observations and optical flow sensors

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Abstract. Flight control of unmanned aerial vehicle relies on three-dimensional attitude determination, and the most commonly used solution is based on the combination of magnetometer, accelerometer, and gyroscope, namely the MARG sensor. Optical flow sensor is also widely applied on UAV to detect the motion of UAV relative to the ground. In this paper, we proposed a novel method that using multiple optical flow sensors to measure angular velocity. This method utilizes a linear model to resolve both linear and angular motion from the measurements of multiple optical flow sensors. In the case of in situ rotations, experiment results prove that the proposed method can effectively estimate the angular velocity, and it can be used to augment MARG-based attitude determination.

1. Introduction

Three-dimensional attitude determination is a prerequisite for flight control of unmanned aerial vehicles (UAV). Over the past decade, the combination of magnetometer, accelerometer, and gyroscope has become the typical sensor configuration for attitude measurement in UAV, which is commonly called MARG sensor [1-3]. With the advances of micro-electro-mechanical system (MEMS) technology, MEMS-based MARG sensor has the advantage of low-cost, low power consumption, and ultra-small size.

MARG-based attitude determination utilizes the observations of three vectors, namely the geomagnetic field, the gravitational acceleration, and the angular velocity. But the measurements of MARG sensor are usually affected by external disturbances, such as the motional acceleration and magnetic interferences [4-7]. Consequently, it is necessary to further enhance the redundancy and robustness of MARG-based attitude determination by introducing auxiliary sensor.

Optical flow, which can be defined as the motion of pixels in image plane, has been widely used for vision-based navigation and motion tracking. In recent years, optical flow sensor has also become a common component in UAV flight control. It can help to acquire motion information of UAV, and thus the accuracy of tracking flight and spot hovering can be improved [8-10].

The measurement of optical flow sensor reflects both the translational and angular motions. But in most studies and applications of optical flow sensors on UAV, the component of angular motion is eliminated using gyroscope, and only the information of translational movement is used. Theoretically, optical flow can also be used to calculate angular motion and attitude, but the existing algorithms involves complicated nonlinear computations [11, 12].
In this paper, we introduce a novel method to measure three-dimensional angular motion using a triad of optical flow sensors. We use a linear measurement model to describe the relationship between the optical flow measurements and angular velocity, which is concise and computationally efficient. We then verify the feasibility of the proposed method by experiment, and its performance is comparable to MARG-based attitude determination.

2. Methodological review

2.1. Attitude determination

Three-dimensional attitude can be described by Euler angles, including heading (also called yaw), pitch, and roll. Quaternion and direction cosine matrix (DCM) are also frequently used to represent 3D attitude. 3D attitude can be directly solved using the geomagnetic vector $\mathbf{h}$ and gravity vector $\mathbf{g}$, e.g. the TRIAD algorithm. Meanwhile, 3D attitude can also be calculated according to the integration of angular velocity $\omega$. To suppress the impact of sensor noise and external disturbances, the above two approaches are usually combined through appropriate data fusion techniques, such as the Kalman filter (KF) and complementary filter (CF) [1-4].

2.2. Optical flow sensor

Fig. 1 shows the commonly used solution using a single optical flow sensor to detect the motion of UAV relative to the ground. The optical flow $\delta$ is actually a 2D vector in the image plane, and its two orthogonal components $\delta_x$ and $\delta_y$ are related to both the linear velocity $v$ and angular velocity $\omega$, as described by (1) [8, 9]. In (1), $d$ is the distance from the camera to the ground, and $f$ is a scale factor. Note that all the components in (1) are in the body frame, i.e. the coordinate system that fixed to the UAV.

$$\begin{align*}
\delta_x &= -f \left( \frac{v_x}{d} + \omega_y \right) \\
\delta_y &= -f \left( \frac{v_y}{d} - \omega_x \right)
\end{align*}$$

(1)

According to (1), an optical flow sensor is only sensitive to the linear and/or angular motion that perpendicular to its optical axis. In other words, a single optical flow sensor can only provide 2D motion information. Therefore, multiple optical flow sensors are needed for measuring 3D angular motion.

3. Motion measurement using optical flow

For a single optical flow sensor, its measurement model can be rewritten as (2), in which $\mathbf{n}$ is a unit vector.
vector along the optical axis, and $v_\perp = v - v \cdot n$ is the component of linear velocity that perpendicular to $n$.

$$\delta = -f \left( \frac{v_\perp}{d} + n \times \omega \right)$$

(2)

Now we introduce another coordinate system for optical flow sensor, namely the sensor frame. The unit base vector triad of this sensor frame is denoted as $\{i, j, k\}$, with $i$ and $j$ located in the image plane, and $k$ along the optical axis. Meanwhile, the unit base vector triad of the body frame is denoted as $\{x, y, z\}$ hereinafter. Using the above symbols, we can further rewrite the optical flow measurement model as (3).

$$\begin{bmatrix} \delta_x \\ \delta_y \\ \delta_z \end{bmatrix} = -f \begin{bmatrix} x \cdot i \\ y \cdot i \\ z \cdot i \\ \hline \\ x \cdot j \\ y \cdot j \\ z \cdot j \end{bmatrix} \begin{bmatrix} (x \times k) \cdot i \\ (y \times k) \cdot i \\ (z \times k) \cdot i \\ (x \times k) \cdot j \\ (y \times k) \cdot j \\ (z \times k) \cdot j \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ v_z \\ \omega_x \\ \omega_y \\ \omega_z \end{bmatrix}$$

(3)

It is clear that (3) shows a linear transformation from $v$ and $\omega$ to the optical flow $\delta$. We can further simplify (3) as (4), with the matrices $U_v$ and $U_\omega$ defined in (5) and (6), respectively.

$$\delta = U_v v + U_\omega \omega$$

(4)

$$U_v = -f \begin{bmatrix} x \cdot i \\ y \cdot i \\ z \cdot i \\ \hline \\ x \cdot j \\ y \cdot j \\ z \cdot j \end{bmatrix}$$

(5)

$$U_\omega = -f \begin{bmatrix} (x \times k) \cdot i \\ (y \times k) \cdot i \\ (z \times k) \cdot i \\ (x \times k) \cdot j \\ (y \times k) \cdot j \\ (z \times k) \cdot j \end{bmatrix}$$

(6)

To acquire complete information of $v$ and $\omega$, we need at least three optical flow sensors numbered as #1, #2, and #3, respectively. Then we will have the measurement model in (7). If these three optical flow sensors are not coplanar, the linear transform matrix in (7) is full rank and thus invertible, i.e. we can calculate $v$ and $\omega$ according to optical flow measurements through linear transformation.

$$\begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \end{bmatrix} = \begin{bmatrix} U_{v1} & U_{\omega1} \\ U_{v2} & U_{\omega2} \\ U_{v3} & U_{\omega3} \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix}$$

(7)

4. Experiment

We use three optical flow modules to implement and evaluate the proposed algorithm. Each optical flow module contains an optical flow sensor PMW3901 and a laser rangefinder V53L1X. Besides, a single-chip MARG sensor MPU9250 cooperates with the optical flow sensors to implement 3D attitude determination. Fig. 2 shows the assembling of optical flow modules. Moreover, an attitude and heading reference system (AHRS) MTi300 is used to provide 3D attitude reference.
To acquire raw data, we hold the experimental apparatus with a certain height from the ground, and then perform in situ rotations. We collect four datasets for the subsequent processing, and these datasets are numbered as Dataset I, II, III, and IV, respectively. Fig. 3 shows the changes of heading, pitch, and roll angles in each dataset. Besides, the height between the optical sensors and the ground for each dataset is listed in Table 1.

It is noteworthy that the linear motion during data acquisition can be neglected, and thus the measurement model in (7) can be simplified as (8), in which $V_\omega$ is a $3 \times 6$ matrix indicating the linear transformation from optical flow to angular velocity.

$$\omega = V_\omega \begin{pmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \end{pmatrix}$$  \hspace{1cm} (8)$$

We use Dataset I to calculate the matrix $V_\omega$ in (8), and then use the calculated $V_\omega$ to get angular velocity from the optical flow measurements in each dataset. Fig. 4 shows the angular velocity that computed according to optical flow (denoted as $\omega_{OF}$), as well as the measurements of gyroscope (denoted as $\omega_{GYR}$). We can find good agreement between $\omega_{OF}$ and $\omega_{GYR}$ in each dataset.
Figure 4. Comparison between the angular velocities from optical flow ($\omega_{OF}$) and gyroscope ($\omega_{GYR}$).

Next, we use $\omega_{OF}$ to replace $\omega_{GYR}$ in KF-based attitude estimation. The root mean square errors (RMSE) of heading, pitch, and roll angles are listed in Table 1.

| Dataset No. | Height to the ground | Attitude estimation using $\omega_{OF}$ | Attitude estimation using $\omega_{GYR}$ |
|-------------|----------------------|----------------------------------------|----------------------------------------|
|             |                      | Heading      | Pitch     | Roll     | Heading   | Pitch     | Roll     |
| Dataset I   | ~1.0m                | 0.96°        | 0.28°     | 0.27°    | 1.19°     | 0.38°     | 0.38°    |
| Dataset II  | ~0.5m                | 0.73°        | 0.24°     | 0.23°    | 0.42°     | 0.24°     | 0.20°    |
| Dataset III | ~1.2m                | 1.01°        | 0.40°     | 0.23°    | 0.82°     | 0.49°     | 0.46°    |
| Dataset IV  | ~0.8m                | 0.80°        | 0.30°     | 0.32°    | 0.64°     | 0.33°     | 0.30°    |

According to Table 1, the RMSE of heading, pitch, and roll remain at the same level when we use $\omega_{OF}$ to replace $\omega_{GYR}$ in attitude estimation. That is to say, the angular velocity computed by the proposed algorithm has comparable accuracy to that of MEMS gyroscope. Furthermore, we can also see that the distance between optical sensors and the ground is irrelevant to the calculation of $\omega_{OF}$, i.e. distance-measuring sensor is not needed for angular motion detection through optical flow.
5. Conclusions
In this paper, we present a linear measurement model of optical flow sensors, which can calculate linear and angular velocities more concisely. With the proposed measurement model and algorithm, we can enhance the robustness and redundancy of UAV flight control based on MARG and optical flow sensors. Moreover, according to the proposed measurement model, it is also possible to implement complete 3D linear/angular motion tracking through a triad of optical flow sensors, and that will be further explored in our future study.

Acknowledgments
This work was financially supported by the Basic Ability Promotion Project for Young and Middle-aged Teachers in Universities of Guangxi under Grant 2019KY0224.

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