센서퓨전과 칼만필터에 기반한 무인항공기의 속도와 위치 추정

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Velocity and Position Estimation of UAVs Based on Sensor Fusion and Kalman Filter

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ABSTRACT

This paper proposes the Kalman filter (KF) with optical flow method to estimate the position and the velocity of unmanned aerial vehicles (UAVs) in the absence of global positioning system (GPS). A downward-looking camera, a gyroscope and an ultrasonic sensor are fused to compensate the measurement from optical-flow method. To overcome the problem of dealing with noise in onboard sensors, the KF is incorporated to efficiently predict the velocity and estimate the position. Basic mechanisms of optical flow and the KF are introduced and experiments are conducted to show how the techniques involved improve the estimations.

1. INTRODUCTION

In recent years, the role of unmanned aerial vehicles (UAVs), especially that of drones, have been becoming increasingly important because they are much cheaper than other existing aerial vehicles. One of the world's leading corporation, Amazon, has announced that it will incorporate drone delivery service named Amazon prime air, which is proposed to deliver products within 30 minutes of delivery anywhere in the US. Many techniques for delivering by UAVs have discussed and widely used to autonomous vehicles [1], [2]. In the near future, we might expect to see drones flying everywhere because technological advancements of drones are happening rapidly, and many governments are willing to make big investments. However, the main concern regarding drones is safety. It can be lethal to people when it gets out of control because it can travel at high speed and altitude. To ensure safety, it is critical to precisely estimate and control the vehicle's position and velocity. This is mainly done through global positioning system (GPS) sensor data, but in indoors, GPS signal can be seriously weakened or completely blocked. Thus, a reliable method of estimation of drone's state in an indoor environment is needed [3].

The information measured by a camera can be used for various applications starting from leader following and automatic landing [4], [5], up to a full three-dimensional mapping of the environment [6]. This work tries to achieve best possible estimation of position and velocity by incorporating three sensors: downward-looking camera, gyroscope sensor, and ultrasonic sensor. Also, it minimizes noise and predict position of the drone from velocity obtained from the sensors by using the KF.

In this paper, we propose a method of estimating the position of UAVs with optical flow method based on the KF. A downward-looking camera, a gyroscope and an ultrasonic sensor are fused to measure the velocity of UAV. From the estimated position with the KF, drawbacks (e.g., noise, uncertainties etc.,) occurred from the onboard sensors can be solved. Algorithm for incorporating the KF and optical flow is proposed, and the performance is demonstrated through the experimental results.

This paper is composed of three sections. Section II introduce theoretical background of the algorithms and techniques, mainly focusing on optical flow algorithm, and the KF. Section III discusses how the experiment have setup and conducted, and Section IV draw conclusions.

2. ALGORITHMS AND TECHNIQUES

A. Optical Flow

Optical flow in short is an algorithm that imitates the way humans perceive moving objects. When a person looks at the outside from a moving car he knows that he is relatively moving forward compared to the trees and houses because all the trees and houses are moving backwards. Optical flow tries to do the same. From two different time-steps, it identifies the pixel that represents the same object and compares positional change of the pixel. If the pixel moved, the algorithm can figure out that the pixel's relative position to the camera has changed.

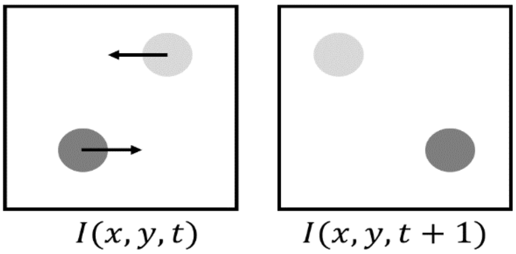

Figure 1. Optic flow problem

In Fig. 1, I is the intensity of the pixel, x and y are coordinates of the pixel, and t denotes the time-step. The optical flow algorithm can identify the pixels that represent the same object (or part of an object) by comparing the color of each pixel. If the two pixels from different time-step has the same color, and the two pixels are close enough in distance, the algorithm concludes that the two pixels are from the same object. This is known as the optic flow problem.

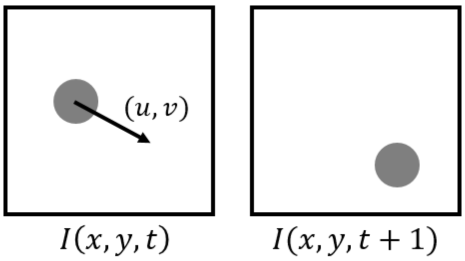

Figure 2. A moving pixel

For optical flow algorithm to work, two assumptions are required. First, there must be color constancy, denoted by I in the diagram, which means that the pixels belonging to the same object point must stay the same color in the next time-step (1) [7]. Second, small motion between two consecutive time-steps is assumed. Since the change in x and y is very small, Taylor Series can be used to approximate the change in I as shown in (3).

$$I(x, y, \mathrm{t}) = \mathrm{I}(\mathrm{x}+u, y+v, t+1), \tag{1}$$

$$0 = I(x+u, y+v, t+1) - I(x, y, t), \tag{2}$$

$$I(x+u, y+v) \approx I(x, y) + I_x u + I_y v. \tag{3}$$

By substituting $I(x, y, t)$ in (2) with (3), the following equations can be obtained.

$$0 \approx I(x, y, t+1) - I(x, y, t) + I_x u + I_y v \tag{4}$$

$$0 \approx I_t + I_x u + I_y v. \tag{5}$$

(5) is the brightness constancy constraint equation which is the main constraint that the algorithm has [4].

B. Compensation with Gyroscope and Ultrasonic

Estimating with optical flow can only be done accurately with support of gyro and sonar sensors [8]. First, height of the camera is required in order to match the movement of pixel on the image to the actual physical distance of the movement.

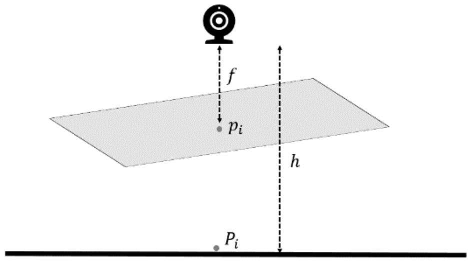

Figure 3. Projection of a single point

In Fig. 3, f is the focal length of the camera, which is the distance where the image is formed, and h is the height of the camera from the ground. By ratio, the actual distance of movement relative to the movement on the image is given by (6)

$$\begin{bmatrix} \square \\ \square \end{bmatrix} = \frac{\square}{\square} \begin{bmatrix} \square \\ \square \end{bmatrix} \tag{6}$$

where P_x and P_y is the point on the real scale, p_x and p_y is a pixel position on the image, and Δ denotes small change. Then, the velocity can be calculated as (7).

$$\begin{bmatrix} v_x \\ v_y \end{bmatrix} = \frac{f}{h} \begin{bmatrix} \frac{\square}{\square} \\ \frac{\square}{\square} \end{bmatrix} \tag{7}$$

In addition, gyroscope sensor data is required to consider angular velocities. The problem with optical flow sensor is that it cannot distinguish translational movements from rotational movements as in Fig. 4.

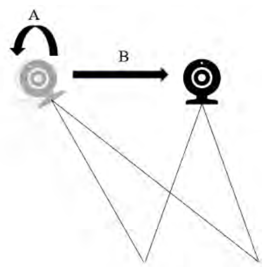

Figure 4. Possible confusion between rotational and translational movement

In Fig. 4, arrow A represents rotational movement and arrow B represents translational movement. In both cases, the change in camera's view is the same even though they are two different movements. Thus, gyro sensor is required to measure angular velocities and compensate the optical flow sensor data. The term $h[w_x \quad w_y]^T$ is added to (7) as a result to form the final equation (8).

$$\begin{bmatrix} v_x \\ v_y \end{bmatrix} = \frac{f}{h} \begin{bmatrix} \frac{\square}{\square} \\ \frac{\square}{\square} \end{bmatrix} + \square \begin{bmatrix} W_y \\ W_x \end{bmatrix}. \tag{8}$$

C. Kalman Filter

The KF is an extremely useful filter to enhance the state estimation process [9], [10]. It is used for two main reasons: to minimize noise in the measurement, and system and to estimate state variables that cannot be directly measured.

The KF can predict state variables including the ones that it did not observe. This is possible due to the prior knowledge of the system. It is stated by physical law that $x_{vel} = \dot{x}_{pos}$ and the KF can be designed to incorporate the relationship. The KF takes the priori estimate $\hat{x}_k^-$ and measured value z_k to calculate the current estimate $\hat{x}_k$ [5], [6]. It uses the Kalman gain K_k to decide which value gets more weight (9).

$$\hat{x}_k = (1 - K_k H)\hat{x}_k^- + K_k z_k, \tag{9}$$

The Kalman gain, however, is not a constant value, but changes by every iteration (10).

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1}. \tag{10}$$

Here, P_k is the error covariance that has the following relationship with the actual value of x (11).

$$x_k \sim N(\hat{x}_k, P_k). \tag{11}$$

To get the next step's priori estimations, we use the following (12) and (13).

$$\hat{x}_{k+1}^- = A\hat{x}_k, \tag{12}$$

$$P_{k+1}^- = AP_k A^T + Q. \tag{13}$$

In (12) and (13), A, Q, H, and R are system model factors that satisfies the following relationships (14), (15), (16), and (17).

$$x_{k+1} = Ax_k + w_k, \tag{14}$$

$$z_k = Hx_k + v_k, \tag{15}$$

$$w_k \sim N(\hat{x}_k, Q_k), \tag{16}$$

$$v_k \sim N(\hat{x}_k, R_k). \tag{17}$$

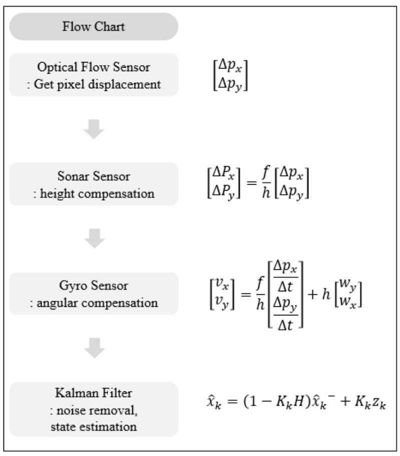

Figure 5. Flow chart of the proposed algorithm

As shown in Fig. 5, four steps are taken to derive the final state estimation of velocity and position. First, the optical flow sensor detects the displacement of pixel, and sonar sensor detects the height and translates the displacement of pixel into physical distance. Then, the gyro sensor executes angular compensation to calculate the velocity. Finally, the KF uses the velocity from the sensors to remove noise and perform state estimation.

3. EXPERIMENT

A. Experiment Settings

The UAV is hovering at a fixed altitude and is moving along a circular trajectory. Quadrotor used is F450, and optical flow sensor used is PX4FLOW v1.3. There is sonar sensor on the bottom, which is LV-MaxSonar-EZ1, and Arduino mega2560 was used for on board computations and network.

B. Experimental Results

The KF is implemented via Matlab, and system parameters were arbitrarily set.

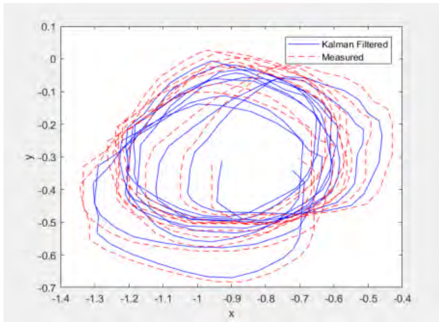

Figure 6. Position measurement and estimation

As noted in the Fig. 6, the red dotted line denotes the position of simply integrating velocity by time, and the blue line represents the position estimated through the KF. In this plot, there is no noticeable different between the two values, but the difference becomes prominent in the two plots below.

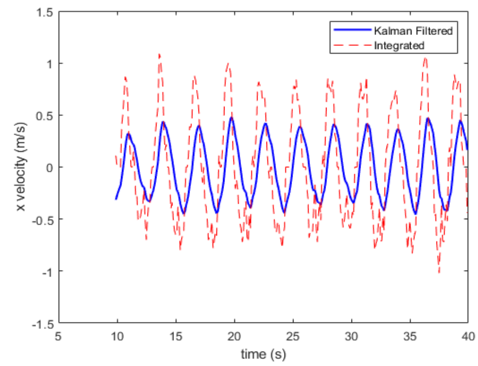

Figure 7. x velocity measurement and estimation

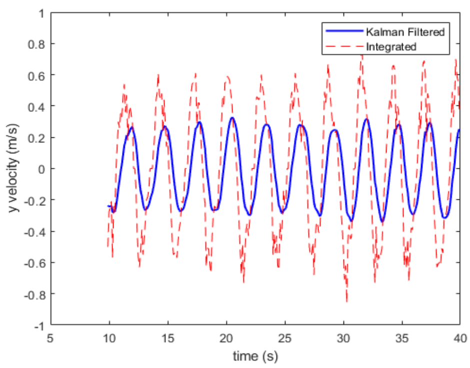

Figure 8. y velocity measurement and estimation

Fig. 7 and Fig. 8 represent the measurements and estimates of x and y velocities, respectively. Red colored lines represent the velocities obtained from the integration of measurements and blue colored lines represent the estimation from the measurements. In these plots, it is clearly seen that the KF stabilizes the unstable values from integration of the sensor measurement. Sinusoidal behavior of x and y velocities is expected from a circular trajectory as shown on plot.

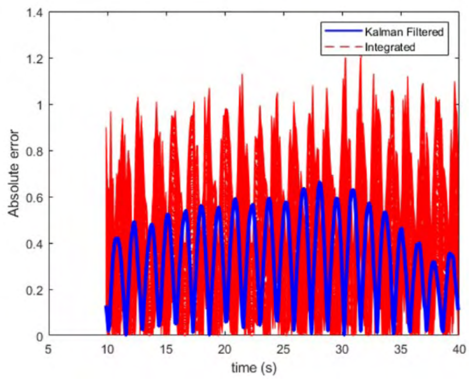

Figure 9. Error of x velocity measurement and estimation

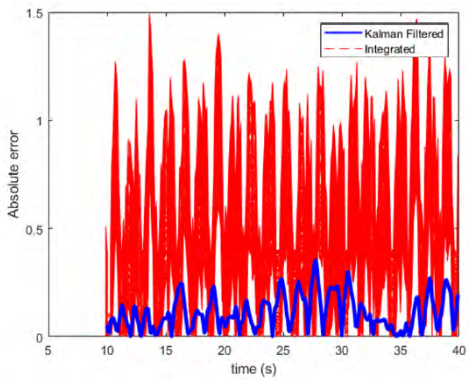

Figure 10. Error of y velocity measurement and estimation

It can be seen from Fig. 9 and Fig. 10 that the error of estimation is significantly smaller than that of integrated values including round-off errors and sensor noises.

4. CONCLUSION

This paper proposes the optical flow algorithms compensated with other sensors and the KF algorithm to estimate the position of UAV. It was seen that the KF effectively reduces noise and estimates position from velocity. Further research of incorporating different sensors is required. Also, there are drawbacks to optical flow algorithms since it cannot detect movement if the image has uniform color across a large area. Therefore, optical flow is not to be used as a standalone algorithm for indoor state estimation. Higher levels of sensor fusion and different methods combined with optical flow is likely to bring the UAV technology to a whole new level.

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