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Estimating the UAVs' Crash Point Based on Optical Flows' Voting in the Image Plane

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Abstract

Towards the actualization of an air bag system for the UAV's crash, this paper proposes a method for estimating the UAV's crash site from the video sequence acquired by the camera attached to the UAV. The crash point can be considered to correspond to the divergence point of the optical flows. In the accumulator, the cells at which the optical flows (straight lines) pass through are incremented by one. After performing this process for all the optical flows, the cell with the largest vote is obtained as the crash point (divergence point) in the image plane. Experiments using a hand held camera show that the accuracy of estimating the crash site is increased as the camera approaches the target plane. Overall, the experimental results are promising.

Introduction

In recent years, UAVs (Unmanned Aerial Vehicles) have been widely utilized in several areas such as shooting videos, surveillance and carrying goods; accordingly, different kinds of UAVs have been developed. There is research to autonomously control UAVs using visual information. [1]–[5] However, a recent serious problem is that the number of UAVs' crashes is increasing. If a UAV crashes, it might hit people, cars, buildings etc.; thereby, it is dangerous and would bring medical treatments or damage compensations problems. Also, if crash happens, the UAV tend to be broken and cannot be used anymore; in this sense, it costs much. Therefore, useful countermeasures for UAVs' crashes are desired.

It might be difficult to avoid UAVs crashes completely. For example, if UAV's propeller is stopped due to unknown cause, a control method for using the other surviving propellers can be utilized[6], but the method cannot support other problems. Even if UAVs crash, if the UAVs are protected somehow, it might be useful. UAVs have started using parachutes as a safe device [7], but safety is not surely kept in case of crashes from low altitudes.

Therefore, we propose an airbag type safety device for UAVs. Ideally, the air bag swells just before the crash; therefore, the air bag can protect not only the UAV itself, but also the human and/or object to be hit by the crashed UAVs. A difficult problem of the air bag for UAVs is that the timing of the swell is critical that since the air bag is swollen by explosion, the bag is deflated quite quickly. That is, even if the air bag is swollen, if it has been already deflated when the UAVs crashes, it is useless.

To avoid the above-mentioned problem, we need to estimate the time point at which the UAVs crashes so that the air bag swells at an appropriate timing, but to our knowledge, no such research has been studied about. Measuring the distance to the crash site by ultrasonic sensors and laser rangefinders can be considered, but basically these measurements can achieve a point measurement; thus, the UAVs does not necessarily fall to that point, which results in wrong crash timing estimation result. In contrast, camera based methods can estimate the crash site (point) in the 2D image acquired by the camera; therefore, the accuracy might be increased. In addition, if we use camera images, we might be able to deal with various environments to be crashed (e.g., flat plane, irregular plane, inclined plane etc.).

This paper aims to achieve a camera-based method for estimating the direction of the crash site as a first step to the achievement of estimating the time point of the crash. The basic idea for the proposed method is that optical flows are considered to be spread out from the point to which the camera (UAV) is heading; therefore, finding such a point is equivalent to estimating the falling direction. From the video sequence acquired by the camera attached to the UAV, optical flows could be detected after the UAV stared falling. By using some filtering, the divergence point, from which optical flows spread, is detecting by a voting scheme based on the orientations of the optical flows.

In the following, the theory of the divergence of optical flows is explained. Then, the proposed method based on the theory is described. After experimental results are presented, this paper is concluded with a discussion and a possible future research direction

Theory

The basic theory of the divergence of the optical flow is shown in Fig 1.This shows the situation in which the UAV is falling to the plane, and at height 1 (higher) and height 2 (lower) the UAV's camera whose optical axis is perpendicular to the plane and observes the plane. The UAV is assumed to fall perpendicular to the plane; therefore, the camera's optical axis and UAV's trajectory coincide. On both sides of the crash point on the plane, two points P_L and P_R are considered. At height 1, the image of P_L is formed at points P_{1L} in the image plane, where P_{1L} is the point at which the image plane and the line segment that connects the optical center of the camera with P_L cross; P_{1L} is represented by p_{1L} in the image coordinate system. Similarly, P_{1R} and p_{1R} are defined. Similarly, at height 2, P_{2L}, p_{2L}, P_{2R}, p_{2R} are defined. The distance between the crash point and p_{1L} (p_{1R}) in the image plane is shorter than the distance between the crash point and p_{2L} (p_{2R}) (See Fig. 1) . That is, if the camera approaches the crash point, the optical flow is oriented outbound from the crash point. This phenomenon occur all the directions: i.e. optical flows diverge from the crash point. This suggests that we should detect the divergence of optical flows to estimate the direction of the UAV's fall.

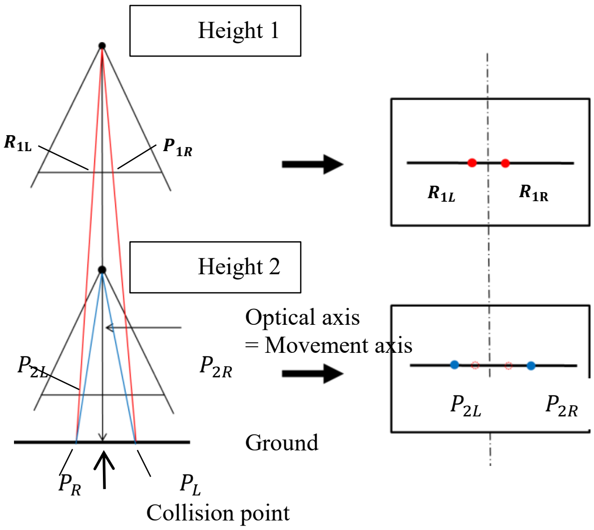


Figure 1. ***Divergence of Flow Vectors point of view when approaching the plane.***

The above-mentioned case, in which both the UAV's trajectory and camera's optical axis are perpendicular to the plane, is defined as Case 1 in Table 1. In Table 1, the horizontal and vertical directions correspond to whether the UAV's trajectory and camera's optical axis coincide or not, and whether the crash site's plane and camera's image plane are parallel to each other or not, respectively. As can be seen in Table 1, four cases are defined. In either case in Table 1, as the camera approaches the target plane, optical flows around the crash point spread outward from the crash point. We called this movement "the divergence of flow". (Fig. 2)

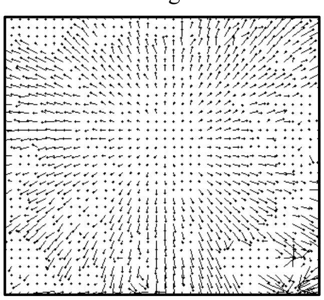


Figure 2. *Divergence of Flow Vectors point of view when approaching the plane.*

Table1. Approach pattern to the target plane of the camera

		The optical axis of the camera matches the moving axis.	
		YES	NO
The target plane and the image plane of the camera are parallel.	Parallel	Case1	Case2
	Not Parallel	Case3	Case4

In fact, the divergence center of the flow merely indicates the intersection of the optical axis of the falling camera and the target plane at each time point. Therefore, the divergence center does not always correspond to the final crash point. Some prediction methods based on the detected divergence centers at multiple time points might be able to estimate the final crash point accurately. Our theory could be useful in case of using a parachute device, because the falling speed at the time of crash is slower by using a parachute,. This paper does not deal with the case in which the UAV falls in a spin.

Proposed Method

The proposed method for estimating the direction of the crash point consists of four steps (Fig 3.).

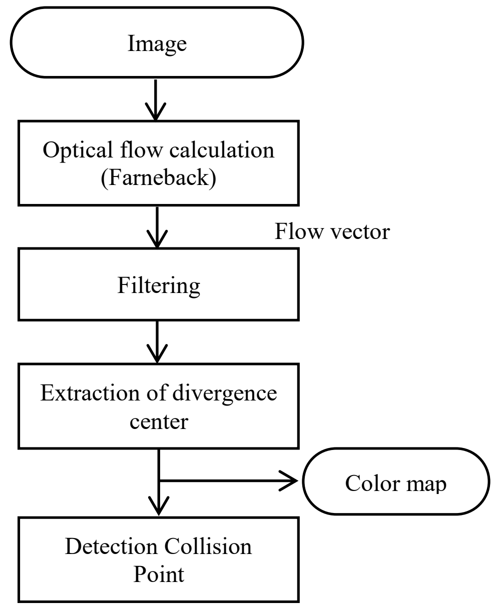
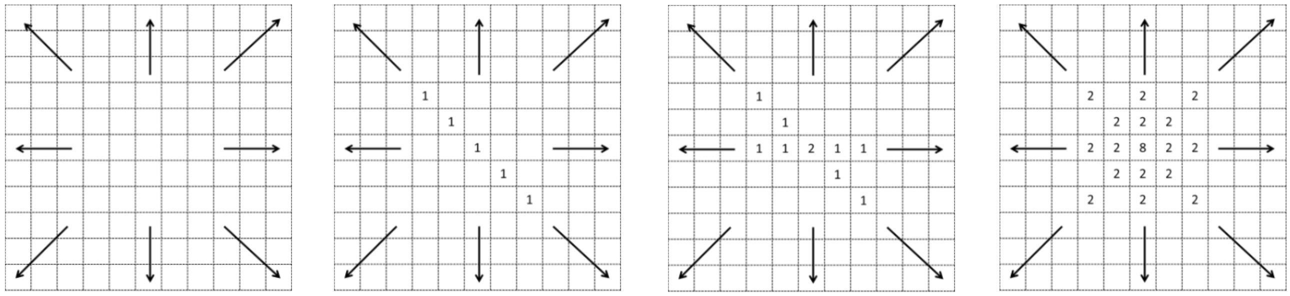


Figure 3. *Our method*

Concerning the Optical Flow Computation in Fig. 3, the optical flow is an effective way to detect motion of an object in video sequences. Typical optical flow detection methods include the Lucas-Kanade method [8] for detect sparse flow and the Gunnar Farneback method for detect dense flow. Our method uses the Gunnar Farneback method [9]. Methods for avoiding obstacles by applying optical flows to on-board camera images have been studied. [10]–[13] Research is being conducted to estimate the distance and speed at the time of the MAVs' landing using the optical flows' information from the images taken by a monocular camera. [13] In this study, the feature points obtained by FAST are tracked by the Lucas-Kanade method. Further, by combining the obtained flow information (divergence) information with the sensor data, the vertical velocity and the vertical distance (altitude) of the MAV are detected from the images taken by the downward camera. However, most conventional studies use camera images only for navigating UAVs, not estimating the crash position.



(a) (b) (c) (d)

Figure 4: *Voting Process: (a) is flow Divergence. If the pixel is on the extension of the flow, one point is added to the pixel. (b) This process votes for all flow extensions. (c-d)*

Filtering

Erroneous flows in the calculated flow are eliminated. We select flows whose magnitude is smaller than 50 pixels. This filtering can be skipped.

Extraction of divergence center

We propose an algorithm to find the center of divergence in the image plane by a voting method. An accumulator, which consists of m by n accumulator cells, is used and initialized (0 is stored to all the cells), where m and n are the pixel numbers in the horizontal and vertical of the image, respectively. Each optical flow is on a straight line, and in the accumulator, the cells which straight line passes through are incremented by one. After this process is performed for all the optical flows, the cell that has the largest votes is obtained as the divergence center. We use Bresenham's line algorithm to shorten the time of the voting process.

Creative Color Map

The result of the voting process is displayed as a color map.

A color map is created based on the accumulator. The vote is represented by color, where the color of the cell is determined by Eq. (1), and the function is shown in Fig5. In the color map, red pixels indicate that there are many votes. Conversely, blue pixels indicate a small number of votes.

$$\text{color value}_{(x,y),n} = \frac{vote\ value_{(x,y),n}}{max\ vote\ value_n} \tag{1}$$

$vote\ value_{(x,y),\mathrm{n}}$ is vote value of each celll, $max\ vote\ value_n$ is maximum votes in the result of the accumulator; n is fram number. The color map can visually represent the location of the divergence center.

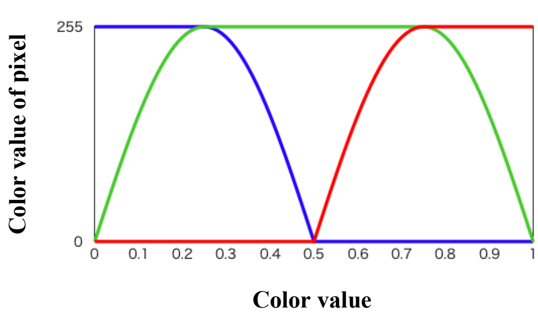


Figure 5: *Graph of function to determine color*

Basic Experiment Results

We use UI-1221-HQ-C from the IDS Corporation as the camera. We conduct experiments to estimate the crash position by the proposed method by approaching the camera to the target plane. The approach pattern is the four cases shown in Table 1.

Color Maps

The color map of the experiment of Case 1 is shown in Fig.7. When the distance between the camera and the plane is far away, our method cannot estimate the crash point accurately (Fig 7. a-b). However, as the camera approaches the plane, our method can estimate the crash point accurately (Fig 7.c). Furthermore, just before the crash, the area of the estimated crash point is enlarged. Due to this, it can be judged that it is just before the crash.

Error Distance

Fig 6 shows the error of the four experiments we performed. We define the distance between the center of the estimated rectangle (collision point area) and the true crash position as the error. The error is calculated by Eq. (2).

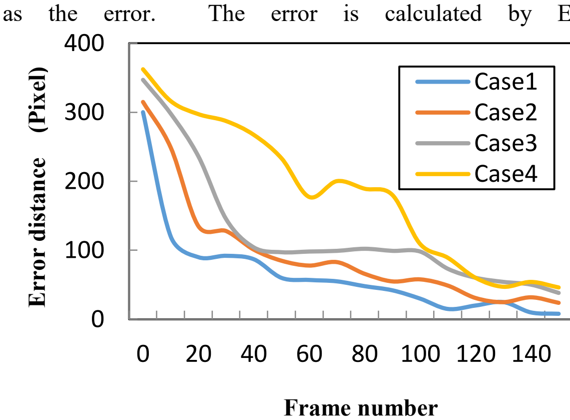
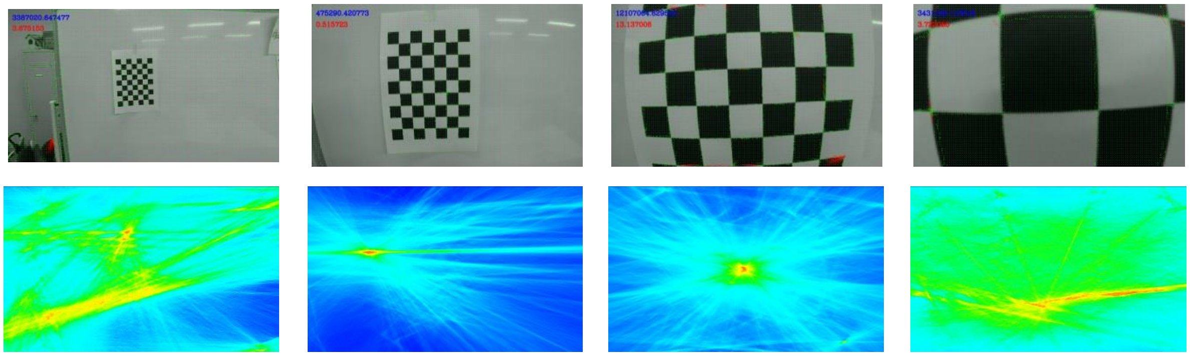


Figure 6. *Results of experiment*

$$\text{error} = \sqrt{(x_{true} - x_{rect})^2 + (y_{true} - y_{rect})^2} \tag{2}$$

In Eq. (2), x_{true} and y_{true} are the center of the rectangle determined by the proposed method. x_{rect} and y_{rect} are the true crash position. The actual crash position of this experiment is the black squares at the center of the checkerboard, and we designate each image.



a. Distance to the surface = 100cm

b. Distance to the surface = 50cm

c. Distance to the surface = 20cm

d. Distance to the surface = 5cm

Figure 7. *Color map: The upper row shows the input image and the lower row shows the output image. The output image is a color map having the same size as the input image. The color map shows the position of the center of divergence. The places with high likelihood are shown in red. The places with low likelihood are shown in blue.*

In all of the four cases in that he experiments were conducted, each crash site is detected accurately as the camera approaches the target plane.

Application to real environment

The proposed method was applied to the camera images taken by the monocular camera mounted on the UAV. Data were recorded using the device shown in Fig. 8,9 for the experiments. We applied the proposed method in a non-real-time system. The camera records images at 40 FPS, and the images share the time stamp with the sensor data (3 axis acceleration, 3 axis angular acceleration, altitude) recorded by the IMU and laser range finder. We raised and lowered the UAV vertically, simulated the crash process. (We assume that UAV's pose is stabilized by expanding a parachute at the time of crash. Therefore, the camera always faces downward.)

Figure 8. *UAV with 6 rotors used in the experiment. We attached the camera and sensor device so that it faces downward at the center of the fuselage.*

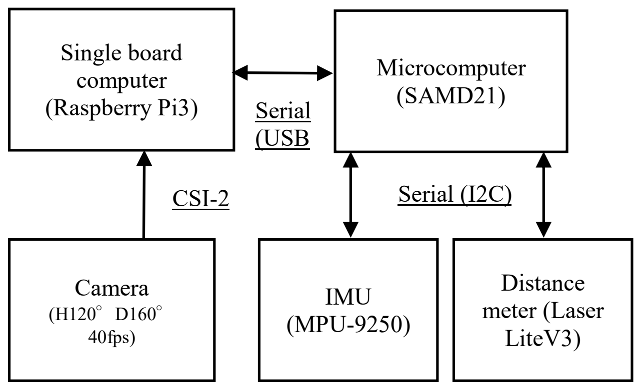
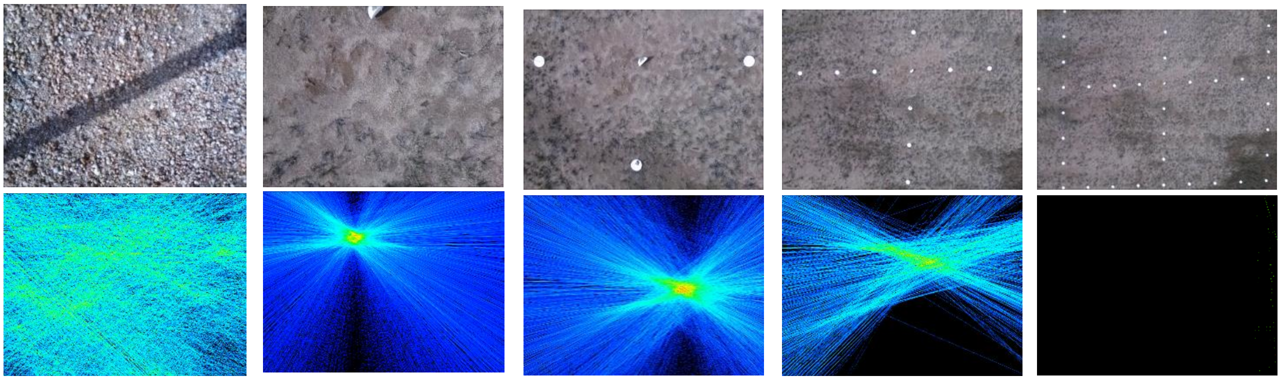


Figure 9. *Configuration of camera and sensor device*

Fig. 10 shows the result of detecting the crash site. Figure 10.a is the image immediately after the UAV takes off. As the optical flow is distributed over the entire screen, the crash point is also detected as a wide range in the image. Fig.10b - e shows the crash site (divergence center). As the altitude increases, the calculated optical flow decreases, and at 7 m altogether no flow was calculated. We confirmed that the proposed method works effectively when the altitude is less than 5.2 m. When the altitude is 5.2 m or more, the movement of the image with respect to the movement of the UAV is small, so the optical flow was not calculated. In order to estimate the timing of crash, we need to select cameras and lenses with optimum angle of view.

On the other hand, when the camera fell and rotated in the yaw axis, the optical flow divergence is hidden by the flow generated by the rotation of the camera. Our method is not effective against this problem. Therefore, we added preliminary processing to correct the rotation of the image by the angular acceleration data of the IMU sensor. As a result of applying rotation correction, signs of problem solving were obtained, but it did not reach a complete solution. In order to solve this problem, we think that noise cancellation of IMU sensor data and a synchronizing system with a complete external sensor are necessary.



a. Distance to the ground= 0m

b. Distance to the ground = 0.5m

c. Distance to the ground = 2m

d. Distance to the ground = 5m

e. Distance to the ground = 7m

Figure 10. *Result of application to real environment: The upper row shows the input image and the lower row shows the output image. The output image is a color map having the same size as the input image. The color map shows the position of the center of divergence. The places with high likelihood are shown in red. The places with low likelihood are shown in blue. White dots in the image are markers set at 1 m interval on the ground.*

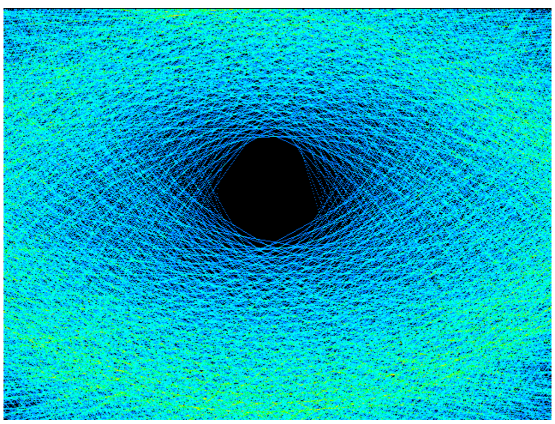


Figure 11. *An image in which the divergence of the flow is hidden by the flow generated by the rotation of the camera.*

Conclusion and Future Work

We have proposed a method for estimating the UAV's crash site in the image when the UAV falls to the plane (ground). The crash point can be considered to correspond to the divergence point of the optical flows. In the video sequence acquired by the camera, optical flows are detected. In the accumulator, the cells which straight line passes through are incremented by one. After performing this process for all the optical flows, the cell with the largest vote is obtained as the crash point in the image plane.

Experiments using a hand held camera show that the accuracy of estimating the crash site (divergence points) is increased as the camera approaches the target plane.

Our future prospect is to fuse the camera and sensors such as the IMU sensor. By correcting the flow when the camera rolls, we aim at improving the detection accuracy.

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