

Vision-based Approach Angle and Height Estimation for UAV Landing

Xiang Pan, De-qiang Ma, Li-ling Jin, Zhe-sheng Jiang
Institute of Information and Communication
Zhejiang University, Hangzhou
Zhejiang, China 310027
madeqiang@gmail.com

Abstract

In order to estimate the approach angle and relative height of Unmanned Aircraft Vehicle (UAV) which lands autonomously, a combinational approach of monocular vision and stereo vision is presented. From monocular sequences, vanishing line is extracted by Hough transform and RANSAC algorithm, and then approach angle of UAV is calculated through vanishing line geometry. From stereo sequences, feature-based matching is adopted to gain depth information by extracting Harris corner. With gained approach angle, height of UAV is obtained by 3-D reconstruction. Kalman filter model is built to obtain accurate height by analyzing motion characteristic of UAV. Experimental results show that the proposed algorithm can effectively estimate the approach angle and height, and converge quickly.

1. Introduction

Landing of Unmanned Aerial Vehicles (UAV) is the last and crucial stage of navigation. Estimating the precise position and orientation of UAV plays an important role in UAV safe self-landing. Vision sensors have low-cost, light-weight and passive features which make them extraordinarily suitable for small UAV.

Frew et al [1] and Srikanth et al [2] have designed special shape platforms for UAV landing. They extract features of these shapes and estimate pose parameters of UAV. These methods cater for the needs of rotor UAV such as vertical take-off and landing. Tung [3] has built an approach angle model when a fixed-wing UAV is landing. Monocular vision is adopted for calculating the UAV's approach angle.

In this paper, we propose a combinational approach of monocular vision and stereo vision. Taking into account that the fixed-wing UAV lands glidingly, the

edge and zebra crossing of the runway are chosen as features. Figure1 is the flow chart of the proposed algorithm. Camera calibration and rectification are processed preliminary. Monocular vision is used to calculate the approach angle of UAV. Hough transform and RANSAC algorithm are used to extract vanishing lines, which improves the accuracy of approach angle following Tung's Model. By Stereo vision, the depth information is got by matching Harris corner extracted from the binocular images. Then post-processing accomplishes to estimate precise parameters. Depth and approach angle are used to calculate the rough UAV height by 3D reconstruction. Further, the accurate UAV height is obtained by Kalman filter algorithm.

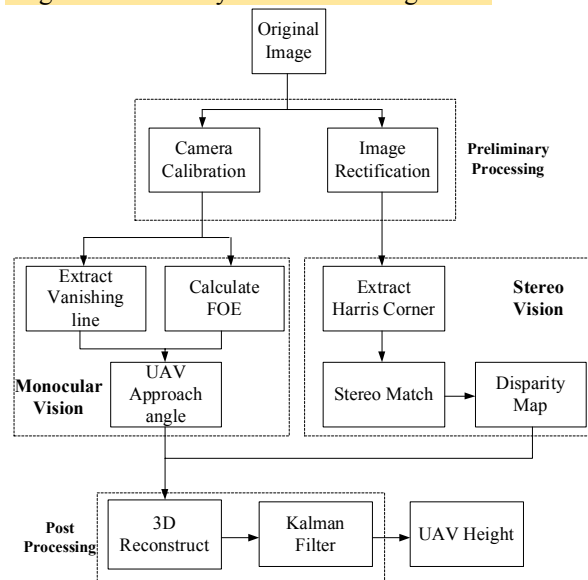


Figure1. Flow chart of the proposed algorithm

The remainder of this paper is organized as follows. Section 2 discusses the method of estimating approach angle using vanishing line geometry, and then stereo vision is used to calculate UAV height in section 3.

Section 4 gives simulation results. Conclusion and future work are discussed in section 5.

2. Approach angle estimation

Approach angle is a very important parameter for UAV landing, which is defined as the angle between the trajectory of the aircraft and the ground surface. To obtain UAV landing information automatically, Tung proposed that 3 parameters are needed to gauge approach angle after camera calibration: field of view center (FOVC), focus of expansion (FOE), and vanishing line of the ground plane. As shown in figure 2, FOVC is the center position of an image; FOE can be derived from the image velocity field. Vanishing line is found by extending the projection of parallel lines. The bottom line is the ground plane, and the upper horizontal line represents a plane parallel to the ground plane and going through the focal point.

Applying trigonometry:

$$\theta = \tan^{-1} \frac{H}{f_p} - \tan^{-1} \frac{L}{f_p} = \tan^{-1} \frac{f_p(H-L)}{f_p^2 + HL} \quad (1)$$

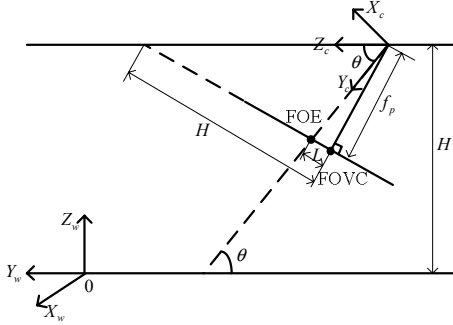


Figure2. Measure approach angle θ

2.1 Extracting FOVC and f_p

Camera calibration is used to seek FOVC and f_p . 2D point is denoted as $\mathbf{m} = [u, v]^T$. A 3D point is denoted by $\mathbf{M} = [X, Y]^T$. We denote the augmented vector: $\tilde{\mathbf{m}} = [u, v, 1]^T$ and $\tilde{\mathbf{M}} = [X, Y, Z, 1]^T$. A camera is modeled by the usual pinhole: the relationship between a 3D point \mathbf{M} and its image projection $\tilde{\mathbf{m}}$ is given by equation (2):

$$s\tilde{\mathbf{m}} = \mathbf{A}[\mathbf{R}, \mathbf{t}]\tilde{\mathbf{M}} \quad \text{with} \quad \mathbf{A} = \begin{pmatrix} \alpha & c & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{pmatrix} \quad (2)$$

Where, s is an arbitrary scale factor; (\mathbf{R}, \mathbf{t}) called the extrinsic parameters, is the rotation and translation which relates the world coordinate system to the camera coordinate system; \mathbf{A} is called the camera intrinsic matrix, and (u_0, v_0) are the coordinates of the principal point, α and β the scale factors in image u and v axes, and c the parameter describing the skewness of the two image axes.

Camera calibration is processed as [4]. It only requires the camera to observe a planar pattern shown at a few (at least two) different orientations. Either the camera or the planar pattern can be freely moved. The motion need not be known. Radial lens distortion is modeled. Compared with classical techniques which use expensive equipment such as two or three orthogonal planes, the proposed technique is easy to use and flexible.

2.2 Extracting vanishing line

Given two cameras fixed at the same level plat, the height of the two cameras ground is the same, vanishing point extracted respectively from the two cameras can determine the vanishing line.

A group of parallel lines have the same vanishing point, so do the edge and zebra crossing of the road paralleled to each other. Hough transform is used to extracts all the edges; RANSAC (RANDOM Sample Consensus) algorithm [6] selects the robust edges to determine the Vanishing Point.

2.3 Extracting FOE

The FOE represents the direction of translational motion. There are two methods to find FOE: Image Velocity Field and Optic Flow Field. As velocity of UAV is fast, and features in images are hard to track by Optic Flow, we choose Image Velocity Field. Harris corners extracted from two consecutive frames are matched to get velocity vectors. Vectors are extended to the whole image, using 3×3 sliding window to get robust FOE.

3. Height estimation

Relative height from UAV to the ground is crucial for UAV landing. After transforming into 2D images, the height information of the objective is lost. Depth from stereo vision and approach angle from vanishing point reconstruct UAV height. Kalman filter model is established to estimates accurate height. The images have been rectified thought epipolar geometry constraint [5].

3.1 Depth from stereo vision

The key part of stereo vision is to find matching points from binocular images, then depth can be derived according to the formula (3).

$$Y_c = bf_p / D \quad (3)$$

Where, Y_c denotes the depth, b is the baseline length between the two cameras, f_p is the focal length of the camera, and D denotes binocular disparity.

There are two classes of matching algorithm: feature-based and region-based. Considering that UAV does not require the whole scene information and the region-based algorithm is time-consuming, feature-based algorithm is selected. Harris corners [8] are then extracted as feature points, for they are sub-pixel and orientation-invariant. We Choose to SSD (Sum of Squared Differences) similarity criteria to match feature points, and then a sparse disparity map is calculated from the equation (3). Results of Harris corner is shown in fig 4.

3.2 3D Reconstruction

In order to establish UAV position in the world, it needs to transform the camera coordinate to world coordinate, as formula (4):

$$\begin{bmatrix} x_w \\ y_w \\ z_w \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta & -\sin \theta \\ 0 & \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} \quad (4)$$

Where, θ is approach angle, x_c, y_c, z_c is the position in camera coordinate. x_w, y_w, z_w is the position in world coordinate. The height of UAV is:

$$z_w = y_c \times \sin \theta + z_c \times \cos \theta \quad (5)$$

The height of UAV will be achieved by statistical average of each depth.

Because some feature points mismatch and system error is unavoidable, the experimental results fluctuates from the true value. The problem will be removed through Kalman filter.

3.3 Kalman filter

Kalman filter [8] is an alternative approach to formulate the MMSE linear filtering problem using dynamic models. UAV landing process can be

approximated to linear movement process. State vector is defined as:

$$\mathbf{y}(n) = \begin{pmatrix} y_p(n) \\ y_v(n) \end{pmatrix} \quad (6)$$

Where, $y_p(n)$ is the height of sampler n. $y_v(n)$ is the UAV speed of sampler n. According to Newton's second theorem, signal model and observation model are as follows:

Signal model:

$$\mathbf{y}(n) = \begin{pmatrix} 1 & T \\ 0 & 1 \end{pmatrix} \mathbf{y}(n-1) + \begin{pmatrix} \frac{T^2}{2} \\ T \end{pmatrix} \eta(n) \quad (7)$$

Where, $\mathbf{y}(n)$ is the state vector of sampler n, T is sampling interval, and $\eta(n)$ is random acceleration.

Observation model:

$$x(n) = (1, 0) \mathbf{y}(n) + v(n) \quad (8)$$

Where, $x(n)$ is the observation value of sampler n, $v(n)$ is the observation error of sampler n.

Initialization impacts on tracking stability of Kalman filter. This paper will set the initial height $y_p(0|-1)$ by 3D reconstruction, rather than simply set it to 0, reducing stable time of the Kalman filter. Initial speed $y_v(0|-1)$ is set to 0 as it can not be obtained directly.

4. Experiment and result

4.1 Experimental platform description

To verify the algorithm, a test platform is constructed. This platform consists of two cameras (JVC1481), clock synchronization card (GL202), image acquisition card (Daheng CQ300), displacement tripod and computer (speeds p4 3.06GHz, memory 512 M), see fig 3. Cameras fixed on the displacement tripod, are moved from top to bottom, which simulates UAV landing.



Figure3. Simulation platform of UAV landing

4.2 Experimental results

Experimental data is handled with Intel's dynamic library OpenCV in Visual C++ 6.0 environment. Captured image size is 320×240. The baseline of stereo cameras is 65cm. Real value of angle and height is obtained by reading scales on the displacement tripod.

Figure 4 shows the results of Hough transform; in which white region simulates an aircraft runway, the gray rectangle of the runway simulates zebra. We can see that Hough transform can effectively extracted the edges. Figure 5 gives detection map of the Harris corner. Reliable corners on zebra are detected, which can improve the accuracy of matching. Average time of image processing is 31.2 ms per frame, see Table 1.

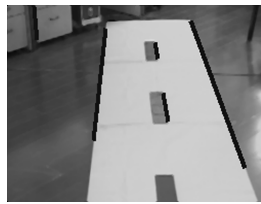


Figure4. Extract edge by Hough transforms



Figure5. Extract Harris corner a) left image
b) right image

Table1 Average time of each image processing

Image Process	Average Time (ms/frame)
Pre-process	3.4
Hough transforms	4.7
RANSAC	6.2
Feature matching	11.9
Kalman filter	1.2
Image show	2.8
Total	31.2

Figure 6 gives the estimated results of approach angle, which is close to the real value. The average error of approach angle is 0.66°. Figure 7 shows the results of height. Dotted line stands for the results for matching feature points, while solid line for the outcome of Kalman filters. The average error after Kalman filter is 1.57cm, the weakest error: 5.97cm. We can see that, feature points mismatch and systematic errors has been effectively conquered by Kalman filter.

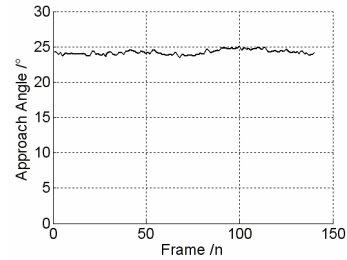


Figure6. Estimation of approach angle

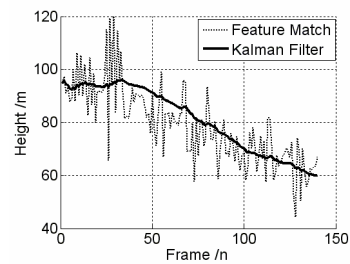


Figure7. Estimation of height

5. Conclusion

Using a combinational approach of monocular vision and stereo vision, approach angle and height of UAV are estimated. Simulation results show that: (1) Based on vanishing Line, the calculation model of UAV approach angle is effective; (2) Height of UAV obtained through 3D reconstruction is consistent with the true value; (3) Using Kalman filtering tracking algorithm can further reduce height error.

The present work is based on UAV simulation platform; the next step is to use real UAV data to verify and improve the algorithm.

Acknowledgments

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