Detection of Obstacles on Runway using Ego-Motion Compensation and Tracking of Significant Features *

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Abstract

This paper proposes a method for obstacle detection on a runway for autonomous navigation and landing of an aircraft. Detection is done in presence of extraneous features such as tire-marks. Suitable features are extracted from the image and warping using approximately known camera and plane parameters is performed in order to compensate ego-motion as far as possible. Residual disparity after warping is estimated using an optical flow algorithm. Features are tracked from frame to frame so as to obtain more reliable estimates of their motion. Corrections are made to motion parameters with the residual disparities using a robust method, and features having large residual disparities are signaled as obstacles. Sensitivity analysis of the procedure is also studied. A Bayesian framework is used at every stage so that the confidence in the estimates can be determined.

1 Introduction

The ability of automatically detecting stationary and/or moving obstacles is essential for autonomous navigation and landing of an aircraft. The existing methods for this task can be classified as either feature based or optical flow based.

In the feature based methods, significant features are detected in the images and matched from one frame to another. An example of this approach is the method proposed by Sridhar et al. [6] to detect and track stationary obstacles on a runway. In this method, features are matched in adjacent frames using normalized correlation. A Kalman filter is then used to track the features in subsequent frames and to produce the range map used to detect the obstacles.

In the flow based methods, an optical flow field is obtained for the entire image. Using the optical flow and the information about the motion of camera, obstacles are detected. For example, in the method proposed by Sull et al. [7], the runway is modeled as a planar surface and an initial model flow field is computed using the data from the inertial navigation unit (INU). Two image frames are warped from one to the other using the given motion and plane parameters. This warping compensates the ego-motion of the features which are stationary and are located on the runway plane as far as the accuracy of these parameters permit. The residual optical flow is estimated and places where this is greater than a threshold are considered for obstacle detection. The residual optical flow at the remaining places is assumed to be due to inaccuracy of the model flow field, and is used to improve the model accuracy. Using the new model, warping is redone, and places where there is significant disparity are signaled as obstacles. This procedure is capable of detecting stationary obstacles located at a height above the runway plane, or moving obstacles. Extraneous features such as tire-marks are also separated.

In this paper, we present a new method that combines the advantages of the feature based and the flow based methods. The proposed method resembles Sull's approach [7] in that warping is used to compensate the ego-motion of the camera. However, instead of finding optical flow over the entire image, features are selected from the image and the optical flow is estimated only at these features. This results in speed up of computation and ease of systematic tracking of features. Furthermore, a statistical framework is used at every step to obtain not only reliable estimates of parameters, but also an estimate of their covariance.

2 System Overview

The system block diagram is shown in Fig. 1. The input to the system is a sequence of images captured from the camera onboard, position and velocity (both linear and angular) of the aircraft obtained from sources such as the GPS and INS, referred here as the Inertial Navigation Unit (INU), and knowledge about the parameters of the runway plane. Using these parameters, a transformation to map features from one frame to another, known as warping, is obtained. Significant features are detected in the image and warped using this transformation. Optical flow, showing the motion of features from frame to frame is obtained from the warped features. Due to warping, the ego-motion of the features on the runway is compensated as much as possible and residual flow is obtained. This makes it easier to detect independently moving obstacles as well as the obstacles with height. Once the optical flow is obtained, features are tracked from one frame to the other, and velocities of the features are smoothed using moving average filtering. The smoothed estimate is added to the warped

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features, so that in the subsequent frames, even this flow is compensated. The estimated residual velocity can then be thresholded in order to check which features are moving or are at a height above the runway plane. Residual velocities of the remaining features can be used to correct the inaccuracies of the warping parameters.

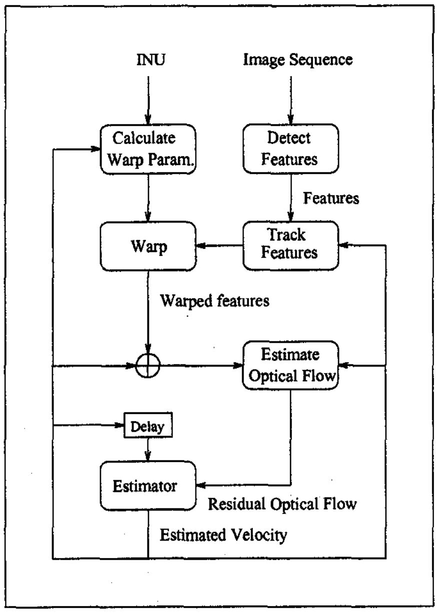


Figure 1: System block diagram.

3 Feature Detection

In the areas of the image where the variance is low, the spatial gradients are also small, and optical flow cannot be computed reliably. Also, due to the aperture effect, full optical flow is unreliable not only in smooth regions, but also in regions where the intensity varies only along one direction. Thus, only features where there is a significant intensity gradient in two perpendicular directions are reliable for determination of full optical flow. Corners satisfy the above condition and are therefore good candidates to use as features. The SUSAN Corner detector [5] developed by Smith and Brady is used to find corner-like features in the image.

4 Warping

The features found above are used to detect obstacles. However, due to motion of the camera, even extraneous features undergo movement from frame to frame. Furthermore, if the range of the feature is unknown, the motion that the feature undergoes cannot be uniquely defined. Hence, features are first assumed to be stationary and on the runway plane, so that their range is unique. The corresponding position of the feature in another frame can then be calculated using the information about the motion of the camera and the equation of the runway plane. Moving obstacles and obstacles at height do not satisfy this constraint, and therefore will have different disparities from what is predicted by this method.

Assuming the origin at the center of perspectivity, the X-axis as the camera axis and the image plane parallel to the Y-Z plane, the perspective projection of the point has image coordinates $(u, v)^T$ given by

$$u = \frac{fy}{x} \text{ , } v = \frac{fz}{x} \tag{1}$$

where f is the focal length parameter of the camera.

Consider that the camera undergoes a rotation R and a translation s so that the coordinates of a point changes from $r = (x, y, z)^T$ in the first frame to $r' = (x', y', z')^T$ in the second frame with

$$r' = Rr + s \tag{2}$$

Let the runway plane be modeled by the equation:

$$n^T r = n_1 x + n_2 y + n_3 z = 1 \tag{3}$$

where $n = (n_1, n_2, n_3)^T$ is the normal vector of the runway plane in the reference frame of the first position. Then, the mapping of the image features on the runway, from the first frame to the second, is given by the warping matrix [7]:

$$A = R + sn^T \tag{4}$$

Thus, the image coordinates (u, v) of a point on the runway plane are mapped to new image coordinates (u', v') according to the following equations:

$$\begin{aligned} u' &= f\frac{A_{21}f + A_{22}u + A_{23}v}{A_{11}f + A_{12}u + A_{13}v} \\ v' &= f\frac{A_{31}f + A_{32}u + A_{33}v}{A_{11}f + A_{12}u + A_{13}v} \end{aligned} \tag{5}$$

Using these equations, features on the runway plane can be warped from one frame to another.

5 Determination of Optical Flow

Discrimination between obstacles and extraneous features on the runway (like tire-marks) can be done by computing the optical flow of the features. Barron et al. [1] have implemented and evaluated several optical flow algorithms in the literature. According to their survey, the method by Lucas and Kanade [2] provides estimation to subpixel accuracy and performs most consistently and reliably over all their test images. Due to these reasons, a modification of this method by Simoncelli et al. [4] that uses a statistical model to account for noise is used. This method not only provides the estimates of optical flow, but also their covariance. The algorithm requires at least five frames, and optical flow is computed in the central frame. Time and space gradients are found at positions of interest and these are used in order to estimate the optical flow.

In our method, local regions around the features which are used to compute the optical flow are warped in all the frames around the center frame. In this manner, the ego-motion of the camera is compensated as much as possible, only the residual disparities are obtained, and warping of the whole image is avoided.

Consider a point in frame t at pixel $w = (u, v)$. The image pixel value at this point is denoted by $F(t, u, v)$. Let $w(t) = (u(t), v(t))$ be a feature in frame t. The warping of this feature in any frame t' is denoted by

$$w(t') = (u(t'), v(t')) = \text{warp}(w(t)) \quad (6)$$

The interpolated pixel value at the position $w(t')$ is mapped to the position $w(t)$ using a bilinear transformation, since $w(t')$ is not an integer in general. Gradients are computed using these interpolated values.

Let the space gradient vector be denoted by $F_s = (F_u, F_v)^T$, the time gradient by F_t and the optical flow vector by $d = (d_u, d_v)^T$. Assuming that the intensity of a point remains approximately constant for the short duration of few frames, the time and space gradients satisfy the gradient constraint equation:

$$F_s^T d + F_t = 0 \quad (7)$$

However, in order to account for inaccuracies, the following probabilistic model is used to estimate the optical flow. [4]:

$$F_s^T(d - \eta_1) + F_t = \eta_2 \quad (8)$$

where η_1 and η_2 are independent zero mean Gaussian noises with covariances given by $\sigma_1^2 I_2$ and σ_2^2. The noise η_1 accounts for errors due to the violation of planarity assumptions and the noise η_2 accounts for errors in the derivative computations.

The full optical flow is determined making the assumption that the flow d is locally constant over a small region around the feature. The time and space gradients are then determined in a window around the feature point.

The maximum likelihood estimate of the optical flow is given by its mean μ_d and covariance Σ_d as follows:

$$\mu_d = -\Sigma_d b \;,\; \Sigma_d = \left[M + \Sigma_p^{-1}\right]^{-1} \quad (9)$$

where

$$\begin{aligned} M &= \sum_{u',v'} F_s(u',v')\sigma^{-2}(u',v')F_s(u',v')^T \\ b &= \sum_{u',v'} F_s(u',v')\sigma^{-2}(u',v')F_t(u',v') \\ \sigma^2 &= \sigma_1^2 \|F_s(u',v')\|^2 + \sigma_2^2 \end{aligned} \quad (10)$$

Σ_p is the prior covariance of the flow and (u', v') lies in the neighborhood of (u, v).

6 Tracking

Once the features are detected in the initial frame, they are tracked over frames. The estimated residual flow is first added to the feature in order to obtain the expected position of the feature in the next frame. Its location is then warped on to the next frame. Hence, if the location of a feature in frame t is $w(t) = (u(t), v(t))^T$, the tracked location is given by:

$$w(t+1) = \text{warp}(w(t) + d(t)) \quad (11)$$

However, instead of using the raw values of optical flow, a moving average of the residual flow is taken. At each frame, the computed residual flow is integrated with the moving average. If $d_s(t)$ is the smoothed estimate of flow in frame t and $d(t+1)$ is the raw flow in frame $t+1$, the smoothed flow in frame $t+1$ is given by:

$$\begin{aligned} d_s(t+1) &= d_s(t) + k(t)(d(t+1) - d_s(t)) \\ k(t) &= \frac{1}{\min(t, 5)} \end{aligned} \quad (12)$$

In this manner, a smoothed estimate of residual flow is obtained. This estimate is added to the warped features, so that in the subsequent frames, even this flow can be compensated.

7 Obstacle Detection

The residual flow nearly compensates the ego-motion for the points on the runway plane and can be used to detect moving obstacles, as well as obstacles which are located above or below the runway plane. However, the accuracy of the parameters used for warping is limited by the accuracy with which the rotation, translation and plane parameters are obtained. Taking this into consideration, two approaches can be taken:

1. Calculate the sensitivity of the warping to the accuracy of the INS and plane parameters. Whenever the residual flow is above the expected deviation, signal an obstacle.
2. Use the residual flow in order to improve the estimate of the warping matrix A. However, a robust method must be used so as to reject the outliers in estimating the parameters.

7.1 Sensitivity Analysis

In order to relate small perturbations in one vector variable to corresponding perturbations in another variable, one can use the Jacobian matrix. Let $y = f(x)$ be an arbitrary vector function of a vector variable x. The Jacobian of y w.r.t. x is denoted here by $J_{y|x}$. Element (i, j) of this matrix is $\partial y_i / \partial x_j$. The chain rule of derivatives can be easily applied to Jacobians using matrix product.

$$J_{z|x} = J_{z|y} J_{y|x} \quad (13)$$

The warping matrix A depends on the camera translation s, rotation R and the plane normal n. Incremental changes in these can be expressed as the linear displacement vector $\Delta s = (\Delta s_1, \Delta s_2, \Delta s_3)^T$, angular displacement vector $\Delta\theta = (\Delta\theta_1, \Delta\theta_2, \Delta\theta_3)^T$ and change in normal vector $\Delta n = (\Delta n_1, \Delta n_2, \Delta n_3)^T$.

Let these parameters be stacked into a single vector Δp given by:

$$\Delta p = \begin{pmatrix} \Delta s \\ \Delta\theta \\ \Delta n \end{pmatrix} \tag{14}$$

and let the matrix A be flattened to give a column vector

$$a = (\; A_{11} \quad A_{12} \quad \dots \quad A_{33} \;)^T \tag{15}$$

Then,

$$J_{d|p} = J_{d|a} J_{a|p} \tag{16}$$

Let the standard deviation in each of the parameters in Δp be given. The covariance matrix formed by these is denoted by Σ_p. Then, the covariance of d is given, in terms of Σ_p, by the equation :

$$\Sigma_d = J_{d|p} \Sigma_p J_{d|p}^T \tag{17}$$

A translating object on the ground is equivalent to a translation of the camera in the opposite direction. Hence, the residual disparity induced by the movement can be estimated by:

$$d = J_{d|p} \Delta p \tag{18}$$

Since only translation is considered, we can write:

$$d = J_{d|s} s_b \tag{19}$$

where $s_b = (s_{b1}, s_{b2}, s_{b3})^T$ is the displacement of the moving obstacle in one frame.

Consider for example, an obstacle crossing the runway. Then, s_{b1}, s_{b3} are nearly zero and the disparity in this case is given by:

$$d = \frac{\partial d}{\partial s_2} s_{b2} \tag{20}$$

In fact, the disparity will mostly be in the horizontal (u) direction. Hence, comparing Σ_{uu} (element $(1,1)$ of Σ) with d_u^2, one can get the threshold velocity which can be detected at a given position in the image,

$$(s_b)_{thresh} = \frac{\sqrt{\Sigma_{uu}}}{\partial d_u / \partial s_2} \tag{21}$$

7.2 Improvement of plane parameters

Since the obtained optical flows are the residual flows after warping using the given A parameters, they represent the error in the flow caused by the error in the A parameters. A Bayesian method can be used to improve the accuracy of A by applying an iterated least squared algorithm.

First note that in equation (5) the warping does not change if the matrix A is scaled by a constant. Thus, A actually has 8 instead of 9 independent parameters. Hence, in order to avoid singularities in the covariance matrices, one can scale a by setting its first element to 1 and scaling the rest of the elements appropriately. The resulting vector can be denoted by:

$$\hat{a} = \frac{1}{A_{11}} (\; A_{12} \quad A_{13} \quad \dots \quad A_{33} \;)^T \tag{22}$$

The Jacobian of the flow w.r.t. this vector is given by $J_{d|\hat{a}}$. Since d is invariant to the scaling of a, the Jacobian can be found by extracting the columns of $J_{d|a}$ except for the first one, corresponding to A_{11}. The $\hat{a}$ vector can then be improved by adding an increment of

$$\Delta\hat{a} = (J_{d|\hat{a}}^T \Sigma_d^{-1} J_{d|\hat{a}} + \Sigma_{\hat{a}0}^{-1})^{-1} J_{d|\hat{a}}^T \Sigma^{-1} d \tag{23}$$

where Σ_d is the covariance of the flow d and $\Sigma_{\hat{a}0}$ is the prior covariance of $\hat{a}$, given by:

$$\begin{aligned} \Sigma_{\hat{a}0} &= J_{\hat{a}|p} \Sigma_p J_{\hat{a}|p}^T \\ J_{\hat{a}|p} &= [\frac{1}{A_{11}} J_{a|p} - \frac{a}{A_{11}^2} J_{A_{11}|p}]_{col2\dots8} \end{aligned} \tag{24}$$

A new disparity can be found using the modified A and the procedure can be repeated until a satisfactory accuracy is obtained. Also, the inverse of the a-posteriori covariance of A is given by:

$$\Sigma_{\hat{a}}^{-1} = J_{d|\hat{a}}^T \Sigma_d J_{d|a} + \Sigma_{\hat{a}0}^{-1} \tag{25}$$

8 Constraint Region Filtering to Separate Moving Objects

The above method detects two kinds of obstacles: moving obstacles as well as stationary obstacles at a height above the ground. In order to distinguish between the two, we use the approach proposed in Tang and Kasturi [8] based on the Nelson's constraint [3]. The main idea in this approach is that in a rigid environment, the projected 3-D velocity of any point in the image is constrained to lie on a 1-D locus in the optical flow space depending only on the camera motion, if the optical flow is exact, or in a region around this locus if the optical flow and/or camera motion parameters are inaccurate.

In order to apply the constraint, the residual flow is taken and the deviation Δd from the constraint locus is found. The covariance Σ_d of the flow is taken as the sum of the covariances due to the error in estimation, and the covariance due to error in the camera parameters. Then, the weighted Mahalanobis norm $\Delta d \Sigma_d \Delta d$ is thresholded in order to locate potential moving obstacles.

The minimum velocity of the moving object can be determined by solving the following equations

$$\Delta d = \frac{\partial d}{\partial s_b} \Delta s_b \; , \; n^T s_b = 0 \tag{26}$$

where s_b is the velocity vector of the object moving on the ground, perpendicular to the normal vector. Note that the actual velocity could be greater than this value, since we have only found the minimum deviation from the constraint, but the actual object could be at a different range.

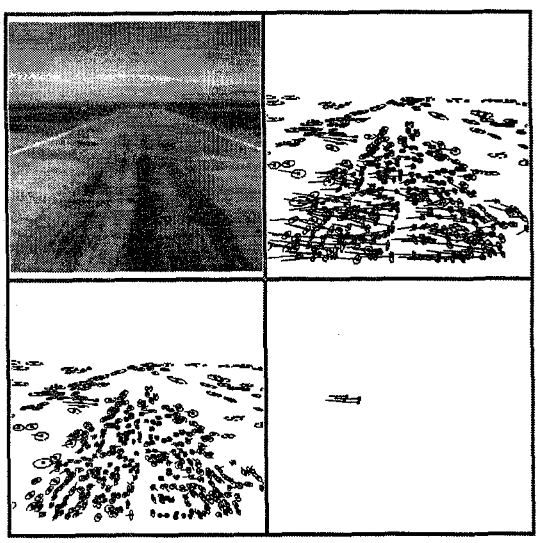
Also, it should be noted that only the obstacles which have a cross component of velocity can be detected. Moving obstacles moving in the same direction as the aircraft, i.e. parallel to the runway cannot be distinguished from a stationary obstacle at a height, due to the inherent ambiguity in monocular image sequences.

9 Observations and results

The method described above was applied to video image sequences captured from a helicopter, and supplied by NASA. Optical flow estimation was first done using the minimum number (five) of frames. In Fig. 2(a), frame number 50 of the image sequence of a truck crossing the runway is shown. It is seen that the image contains numerous extraneous features such as tire-marks in addition to the moving truck, making the task more difficult. The raw feature flows are shown in Fig. 2(b). The plane parameters were estimated using these flows and the flows were corrected using the improved parameters. The resulting flows are shown in Fig. 2(c). In both figures, the estimated covariance ellipses are also shown, magnified 5 times for clarity while the flow vectors are magnified 25 times. The feature flows were then thresholded using the Mahalanobis norm w.r.t their covariances. The truck was easily detected as shown in Fig. 2(d).

To verify the tracking of features, fifteen frames were used, with frame 50 as the center frame. A zoomed part of the original image is shown in Fig. 3(a). The tracked features and their smoothed velocity estimates are shown in Fig. 3(b) and Fig. 3(c), respectively. The covariance ellipses are also shown and the magnifications are the same as in the previous case. The results after thresholding in a similar manner are shown in Fig. 3(d).

(a) (b)

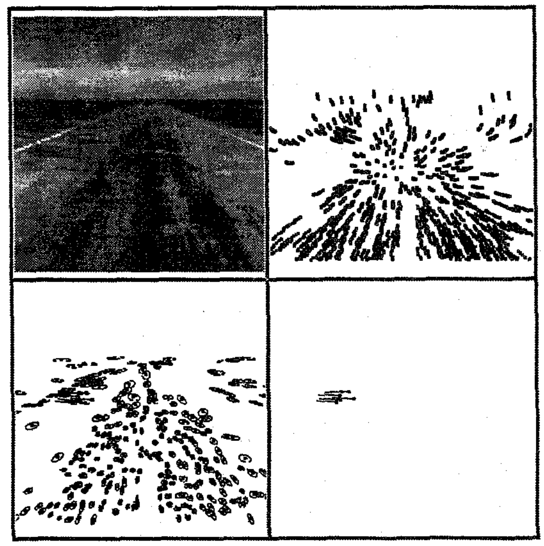


(c) (d)

Figure 2: Detection of obstacle using minimum number of frames: (a) Original image (b) Estimates of residual optical flows (unsmoothed) with covariance ellipses. (c) Estimates after improving warping parameters (d) Detection of moving truck.

Nelson's constraint was applied on the smoothed velocity estimates of Fig. 3. The shortest distance measure Δd, which show the deviation from Nelson's constraint are shown in Fig. 4(a), along with the covariance ellipses. Thresholding was done on these showing the detected truck in Fig. 4(b).

(a) (b)



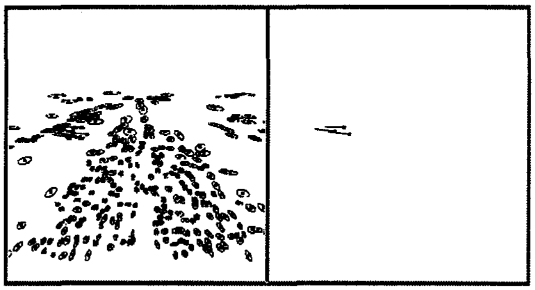
(c) (d)

Figure 3: Detection and tracking of obstacles using large number of frames: (a) Original image (b) Tracked features in the sequence of images (c) Estimate of residual feature velocities (smoothed) (d) Detection of moving truck.

A study of the propagation of uncertainty from motion and plane parameters to the optical flow was also performed. In our experiments, it was observed that the range of points on the runway plane changed more significantly in the vertical (v) direction in the image. The uncertainty of the optical flow is plotted against the row value, (with column value constant $u = 256$) in Fig. 5(a). For comparison purposes, the theoretical flow induced by a moving obstacle is also plotted. The obstacle can move in the cross direction, or parallel direction. The flow induced by each of these movements at the rate of 1 $ft/frame$ is also plotted against the row value in in Fig. 5(b) and (c).

10 Summary and Future Work

In this paper, we proposed a method for detection and tracking of obstacles on a runway for autonomous navigation and landing of aircrafts. Significant features were detected on the runway and residual optical flow was obtained. Warping was performed so that the ego-motion of the features was compensated as much as possible. However, due to the inaccuracy of the given parameters, full compensation was not possible. Hence, a sensitivity analysis of the warping to the variation of the given parameters was studied. A method to improve the accuracy of the warping using the residual disparities was also proposed. Application of this method to a runway image sequence was



(a) (b)

Figure 4: Application of Nelson's constraint : (a) Shortest distance measure Δd along with estimated covariance showing the deviation from Nelson's constraint. (b) Thresholding of the shortest distance. Truck is detected, but there are false alarms.

demonstrated and it was shown that obstacles can be separated from numerous extraneous features such as tire-marks.

Future work includes improvement and testing of each of the above stages for different image sequences under various conditions. Also, sensor fusion methods to combine the information available from different sources such as the GPS, the INS, and landmarks like lines and beacons on the runway, to obtain better estimates are being explored.

References

[1] J. Barron, D. Fleet, S.S.Beauchemin, and T. Burkitt. Disparity analysis of images. In *Proc. IEEE Computer Vision and Pattern Recognition*, volume 2, pages 236–242, 1992.

[2] B. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. In *DARPA Image Understanding Workshop*, pages 121–130, 1981.

[3] R. C. Nelson. Qualitative detection of motion by a moving observer. In *Proc. IEEE Computer Vision and Pattern Recognition*, pages 173–178, 1991.

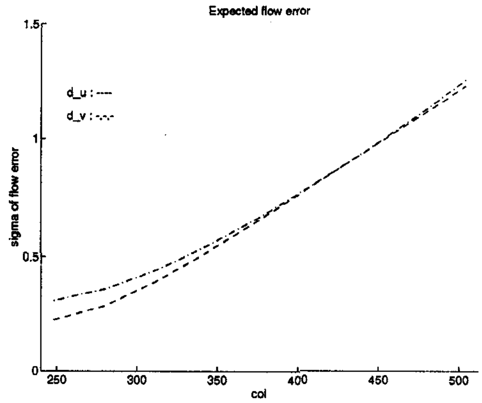
[4] E. P. Simoncelli, E. H. Adelson, and D. J. Heeger. Probability distributions of optical flow. In *Proc. IEEE Computer Vision and Pattern Recognition*, pages 310–315, 1991.

[5] S. Smith. A new class of corner finder. In *Proc. 3rd British Machine Vision Conference*, pages 139–148, 1992.

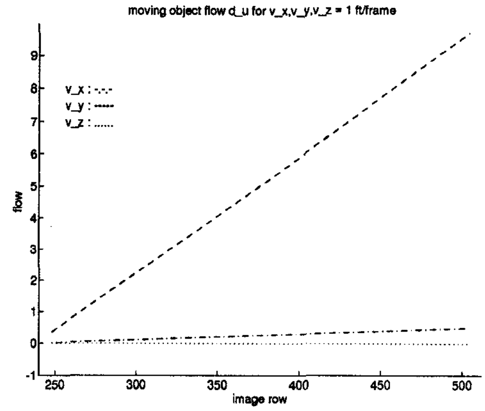
[6] B. Sridhar, R. Suorsa, and B. Hussien. Passive range estimation for rotorcraft low-altitude flight. *Machine Vision and Applications*, 6:10–24, 1993.

[7] S. Sull and B. Sridhar. Runway obstacle detection by controlled spatiotemporal image flow disparity. In *Proc. IEEE Computer Vision and Pattern Recognition*, pages 385–390, 1996.

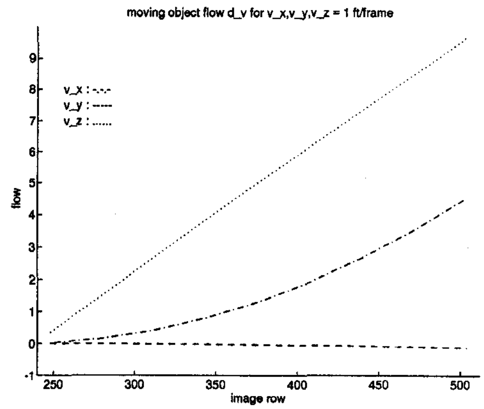
[8] Y.-L. Tang and R. Kasturi. An airborne vision system for runway recognition and obstacle detection. Technical Report CSE-94-045, Department of Computer Science and Engineering, Penn State University, August 1994.



(a)



(b)



(c)

Figure 5: Sensitivity Analysis of flow to camera and object motion parameters: (a) Plot of standard deviation of error in u and v directions against the v values for u = 256. (b),(c) Plots of the optical flow in u and v directions induced by the movement of obstacle in x, y, z directions u flow. (d) Plot of threshold velocity of an object against the v image coordinate for different values of the uncertainty in flow