CICLOPE : A Normal Flow based Approach for Real Time Obstacle Detection

Vitor Costa Marco Sentieiro José Santos-Victor
Instituto de Sistemas e Robótica & Instituto Superior Técnico,
Av. Rovisco Pais, 1096 Lisboa Codex, PORTUGAL
e-mail jasv@kappa.ist.utl.pt

1 Introduction

This paper addresses the problem of visual based mobile vehicle navigation, particularly at the obstacle avoidance level. In order to minimize the latency in the system response to the presence of an obstacle, the method proposed here is a kind of reflexive behaviour designed to solve this particular task, rather than achieving scene reconstruction and obstacle segmentation.

The main assumption used in the design, is that the robot is moving on a flat ground plane. Another important feature of this method, apart from the purposive approach, is the use of partial information of the optical flow, as the input. All the different steps are exclusively based on the normal flow field which can be estimated fast and robustly.

There is no need to calibrate the camera parameters or position and we present some results of a real time application.

2 Normal flow based obstacle detection

If the robot is moving on a ground floor, with the camera pointing downwards, then the perceived image velocity pattern is constant in time provided that the motion parameters do not change. This feature can be used for a fast obstacle detection procedure [2].

Under the hipothesis of planar motion [7], there is a global model for the expected optical flow field. The model parameters, in turn, can be initially estimated using the image first order time/space derivatives (or equivalently the normal flow), which convey information both about the robot motion and the plane orientation and position. During operation, we use the residues of the fundamental optical flow constraint with the estimated image derivatives to detect obstacles lying outside the ground plane.

We assume that only the normal component of the flow field is available, as it is well known that estimating both components of the optical flow [1, 4] is a very hard problem and the results are often extremely sensitive. Assuming that the image brightness (of each point) is constant over time, the optical flow constraint equation is given by [3]:

$$g_x u + g_y v + g_t = 0 \tag{1}$$

where g_x, g_y and g_t stand for the image first order space and time derivatives. With this constraint, it is only possible to obtain the flow component in the direction of the image gradient (aperture problem).

2.1 Affine motion estimation using the normal flow

Let us assume a pinhole model for the camera and a rigid body motion model for the robot where $\mathbf{T} = [T_x \; T_y \; T_z]^T$ and $\boldsymbol{\omega} = [\omega_x \; \omega_y \; \omega_z]^T$ are the translational and angular velocities respectively. The motion perceived in the image plane by the moving camera is then given by the well known equations :

$$\begin{bmatrix} u \\ v \end{bmatrix} = \frac{1}{Z} \begin{bmatrix} -f & 0 & x \\ 0 & -f & y \end{bmatrix} \begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix} + \begin{bmatrix} \frac{xy}{f} & -f - \frac{x^2}{f} & y \\ f + \frac{y^2}{f} & -\frac{xy}{f} & -x \end{bmatrix} \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \tag{2}$$

where f is the camera focal distance and Z is the distance to the 3D point visualized [6]. Assuming that the robot is moving on a ground plane, with the camera pointing at the ground floor, a global model for the motion field can be found :

$$\begin{aligned}\begin{bmatrix} u \\ v \end{bmatrix} &= \begin{bmatrix} Ax+By+C & 0 & -Ax^2-Bxy-Cx \\ 0 & Ax+By+C & -Axy-By^2-Cy \end{bmatrix} \begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix} + \\ & \begin{bmatrix} xy & -1-x^2 & y \\ 1+y^2 & -xy & -x \end{bmatrix} \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \end{aligned} \tag{3}$$

where the plane equation is given by:

$$\frac{1}{Z} = -Ax - By - C \tag{4}$$

and A, B, and C are the plane parameters. Rearranging eq. (3) we can obtain a global model for the optical flow field as :

$$\begin{aligned} u &= u_0 + u_x x + u_y y + u_{xy} xy + u_{xx} x^2 \\ v &= v_0 + v_x x + v_y y + v_{xy} xy + v_{yy} x^2 \end{aligned} \tag{5}$$

Directly estimating the parameters of this model is usually not robust as it is known that the second order parameters estimates can be affected by noise up to several orders of magnitude higher than the first order parameters estimates. On the other hand, for a limited field of view and reduced depth of field, the second order terms can be neglected. An important improvement on robustness, and accuracy can be attained if we assume an affine model for both components of the flow :

$$\begin{aligned} u &= u_0 + u_x x + u_y y \\ v &= v_0 + v_x x + v_y y \end{aligned} \tag{6}$$

Replacing the terms u and v on the first order constraint (1), we obtain :

$$u_0 g_x + u_x g_x x + u_y g_x y + v_0 g_y + v_x g_y x + v_y g_y y = -g_t \tag{7}$$

Therefore, the temporal derivative can be expressed as a linear combination of the parameters to estimate:

$$\begin{bmatrix} g_x & xg_x & yg_x & g_y & xg_y & yg_y \end{bmatrix} \boldsymbol{\theta} = -g_t \tag{8}$$

where $\boldsymbol{\theta}$ is given by:

$$\boldsymbol{\theta} = \begin{bmatrix} u_0 & u_x & u_y & v_0 & v_x & v_y \end{bmatrix}^T \tag{9}$$

The parameter vector, $\boldsymbol{\theta}$, is estimated using a least squares method, associated with an iterative procedure to avoid the influence of outliers due to noise on the calculation of the image derivatives as suggested in [5].

The pattern flow is now obtained directly from eq. (6) and is independent of the camera intrinsic parameters. Although the whole estimation process is highly dependent on the camera velocity, it can be shown that if the initialization procedure is done for both, pure translational and rotational motions, and if the velocities are known, it is possible to develop a solution for the pattern flow which is valid for any motion of the platform.

2.2 Dealing with general motion

The method we propose can easily be applied with general simultaneous angular and linear robot velocities, simply by introducing a two step initialization procedure.

We start by determining the flow pattern, $\mathbf{u}_{rot}$, for pure robot rotation $\boldsymbol{\omega}_p$. We also estimate the flow pattern $\mathbf{u}_{trans}$, for pure robot translation $\boldsymbol{T}_p$. If the robot is moving with general motion $\alpha\boldsymbol{T}_p$ and $\beta\boldsymbol{\omega}_p$, then the resultant flow is simply given by $\alpha\mathbf{u}_{trans} + \beta\mathbf{u}_{rot}$. Therefore, provided that α and β are known, the reference flow pattern can still be retrieved from the original initialization data.

2.3 Obstacle Detection

As explained before, the method proposed here relies on the fact that the robot is moving on a flat ground plane. Therefore, given the robot motion parameters, the expected flow can be determined for every point lying on the ground plane. Any obstacle located above or below the pavement will exhibit a different flow.

Using the method described in the previous sections, when the robot is moving, we can determine the expected flow, u and v, and check for inconsistencies to detect obstacles. The obstacle detection method is based again on the information of the normal flow or, equivalently, the first order time-space derivatives g_x, g_y and g_t. For every point on the ground floor the following equation should be satisfied :

$$g_x u + g_y v + g_t = 0 \tag{10}$$

The residue of this equation is tested to detect the presence of obstacles.

3 Results

This section shows some results obtained using the method proposed. In the first experiment the camera moves in front of a background parallel to the image plane along the horizontal direction. The distance to the back plane is about 30cm and the object and the background have similar textures. The input images are shown in Figure 1. Figure 2 shows the normal flow computed during the initialization phase

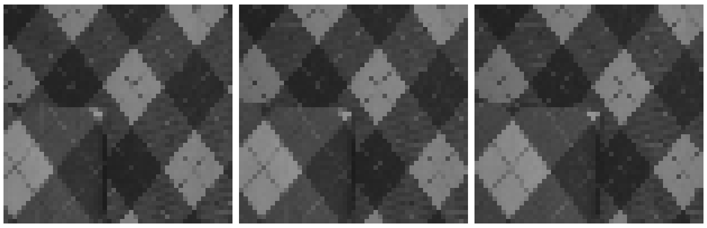

Figure 1: Image sequence with an obstacle (1, 3 and 5th of the sequence).

(without obstacles), together with the normal flow in the obstacle scene and finally, the detected obstacle areas.

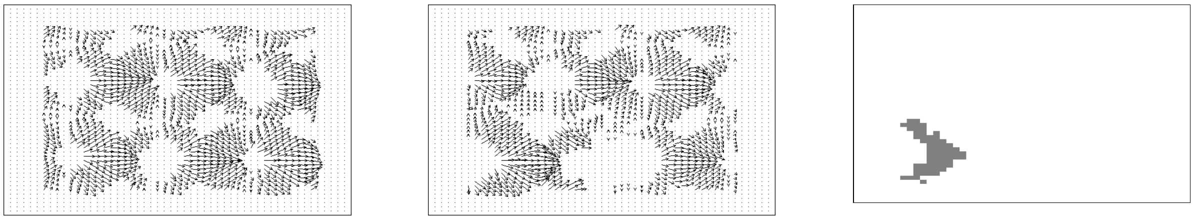

Figure 2: Normal flow of the ground plane, normal flow with the obstacle and detected areas.

Many tests were performed using a TRC Labmate mobile platform, with a camera having a 4.8mm lens. The camera was placed in the front pointing down at about 45 degrees. The image resolution is 49x51 pixels. The platform moves at 50mm/s, the images are acquired at 5Hz. The current implementation of the system runs at a frequency between 1Hz and 2.5Hz (depending on the choice of the image sampling rate). Figure 3 shows the experimental setup together with the input image sequence with an obstacle.

On Figure 4 we show the estimated reference flow pattern determined in the initialization phase, the normal flow field during normal operation and the detected obstacle regions.

4 Conclusions

This paper describes a method for fast obstacle detection for mobile robots, based on the normal flow field. The basic assumption is that the robot is moving on a ground floor and any object lying out of

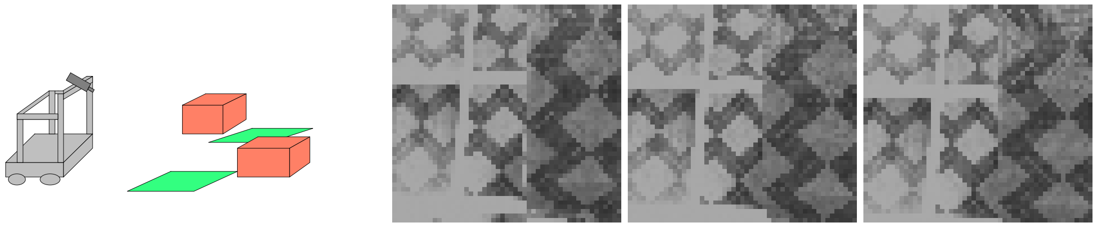

Figure 3: Experimental setup and the input image sequence with an obstacle.

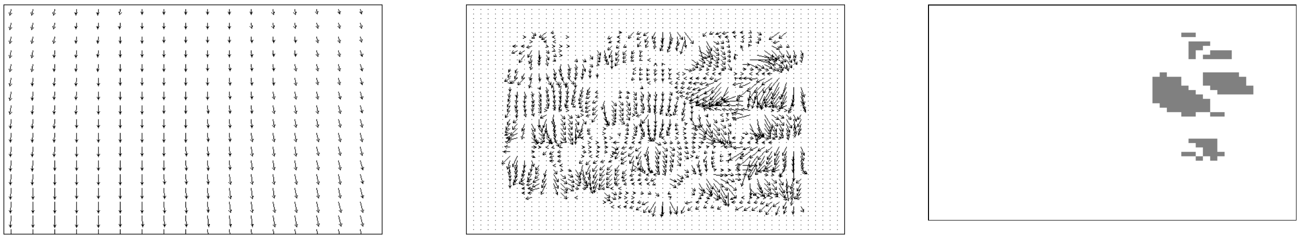

Figure 4: Estimated reference flow pattern; normal flow for the sequence of Figure 3; and detected obstacle regions.

this plane is considered as an obstacle.

The optical flow of the ground floor points is described by an affine model. The model parameters are estimated using exclusively the first order time and space derivatives, or equivalently the normal flow. For the obstacle detection phase, the residues of the fundamental optical flow constraint are tested.

There is no need to explicit calibrate the camera intrinsic or extrinsic parameters. The method can be used under general motion of the robot. The performance achieved is significantly improved by the use of qualitative information of the optical flow, as there is no need to recover both optical flow components. We present several real time experiments, using a mobile robot, illustrating the robustness of the approach.

References

[1] J.L. Barron and D.J. Fleet and S.S. Beachemin, Performance of Optical Flow Techniques. International Journal of Computer Vision, 12(1):43-78, 1994.

[2] F. Guarnotta and D. Rizzieri F. Tarocchi and M. Tistarelli and G. Sandini, Studio di un Problema di Obstacle Avoidance per un Robot Mobile. Internal report - DIST University of Genova, 1992.

[3] B. Horn and B. Shunck, Determinig optical flow. Artificial Intelligence, 17:185-203, 1981.

[4] H.H. Nagel, On the Estimation of Optical Flow: Relations between Different Approaches and Some New Results. Artificial Intelligence, 33:299-323, 1987.

[5] J. Santos Victor and G. Sandini, Uncalibrated Obstacle Detection using Normal Flow. submitted, 1994.

[6] J. Santos Victor and J. Sentieiro, A 3D vision system for underwater vehicles : an extended Kalman-Bucy filtering approach. NATO-ASI on Acoustic Signal processing for Ocean Exploration, Portugal, 1992.

[7] D. Sinclair and A. Blake and S. Smith and C. Rothwell, Planar Region Detection and Motion Recovery. British Machine Vision Conference, 1992.