Estimation of Visual Motion Parameters Used for Bio-inspired Navigation

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Abstract—Visual motion cues play an important role in animal and humans locomotion without the need to extract actual ego-motion information. This paper demonstrates a method for estimating the visual motion parameters, namely the Time-To-Contact (TTC), Focus of Expansion (FOE), and image angular velocities, from a sparse optical flow estimation registered from a downward looking camera. The presented method is capable of estimating the visual motion parameters in a complicated 6 degrees of freedom motion and in real time with suitable accuracy for mobile robots visual navigation.

Index Terms—time-to-contact, focus of expansion, image angular velocity, optic flow models

I. INTRODUCTION

A. Motivation

Since Gibson’s work in [1] visual information and optic flow have been gaining increasing research interest in order to understand and solve visual locomotion problems. Gibson has highlighted the importance of some of the visual motion parameters like the location of the Focus of Expansion (FOE) and the dilation of optic flow to avoid or achieve a contact with an object. Image dilation plays an important role in estimating the Time-To-Contact (TTC) with observed objects [2]. Image angular velocity of ventral flow has been found to be employed by bees to regulate their speed and and distance to surrounding walls and their height while landing [3].

Such studies highlighted the importance of visual motion parameters and their role in locomotion without the need to estimate actual motion parameters such as the velocity or the position or even the knowledge of the structure of the scene. Many robotics systems implementations exploited only visual motion information to achieve autonomous navigation. Image angular velocity has been used in [4] [5] to achieve horizontal autonomous landing. Image dilation has been used by [6] to achieve vertical landing. FOE and TTC have been used in [7] to implement a collision warning system and by [8] to implement a visual collision avoidance algorithms for mobile robots.

B. Related Work

A good deal of work has been done on the estimation of the ego-motion parameters from an image sequence. A method proposed by the authors in [9] involves the calculation of the direction of motion, effectively the FOE, from the optic flow difference at points representing edges of depth variations, then use this point to calculate the motion angular velocity and the depth map, but not image angular velocities. This requires a dense cluttered scene and a reliable method of calculating the optic flow on such points. Heeger and Jepson [10] proposed a method to retrieve the translational and rotational motion as well as a depth map of the scene by solving for the direction of motion from a sub-sampled solution space then solving for rotation and depth. Their proposed method adds an unwanted complexity to retrieve the actual ego-motion parameters and depth map and their off-line computed coefficient scheme requires the optic flow estimates at constant points, something that might introduce bad optic flow measurements if such points have low contrast. A recursive method proposed by Barron and Eagleson [11] to solve for the translational and rotational ego-motion velocities, angular acceleration as well as depth map. The method is only tested in a restricted motion profiles where rotation takes place on one axis only.

Camus in [12] presented a method of solving for the FOE then the time-to-contact. He calculates the FOE by averaging the translational optic flow signs along the horizontal and vertical image directions separately. Then he calculates the time-to-contact from rate of expansion of optic flow from the FOE assuming that the motion is straight forward with no lateral motion. Similar approach taken by Sund are swaran et al. [7] to calculate the FOE and the TTC using the more reliable normal optic flow measurements. Both methods prefer a uniform distribution of optic flow measurements for an unbiased FOE location. They also assume a forward only motion for the FOE, and hence the TTC, to be calculated correctly.

A mathematical framework for computing the TTC and the camera angular velocities is presented by Micheli et al. [13]. The method finds the motion parameters from the eigenvalues of the Jacobian of the optic flow evaluated at the FOE. Unfortunately the most general motion this method can handle is an axial motion with
rotation axis constant and coincides with the translation axis besides it does not demonstrate a method for calculating the image angular velocities.

A method for calculating the FOE has been proposed by Teshima et al. [14] that does not rely on optic flow. Instead, the method iteratively estimates the expected new video frame from the previous frame and a motion model that depends on the location of the FOE by minimizing the sum of absolute differences (SAD). Direct gradient based methods exploiting brightness constancy have been used to calculate the TTC without feature tracking in [15], however only translational motion of the observer and viewed object V has been defined by Srinivasan et al. [3] as:

\[ u = -f \frac{V_x}{Z} + x \frac{V_z}{Z} \]
\[ v = -f \frac{V_y}{Z} + y \frac{V_z}{Z} \]

which is only defined when \( V_z \) is non-zero. From (3, 4, 5) the optical flow translational velocities can be written as

\[ u_T = -f \frac{V_x}{Z} + x \frac{V_z}{Z} \]
\[ v_T = -f \frac{V_y}{Z} + y \frac{V_z}{Z} \]

In this case the FOE is the only point where the optic flow vectors all coincide; hence it will be the only vanishing point of the optical flow vectors. We can find the image point coordinated \( x_{foe}, y_{foe} \) of the FOE from (3) and (4) by setting the optical flow vectors and angular velocities to zero.

\[ x_{foe} = f \frac{V_z}{V_x} \]
\[ y_{foe} = f \frac{V_y}{V_z} \]

which shows that the translational optical flow vectors exhibit pure dilation about the FOE. Equations (6) and (7) show the direction relationship between optical flow estimation and the direction of motion presented by the FOE as well as the TTC presented by image dilation d given by:

\[ d = \frac{V_z}{Z} \]

which is clearly the inverse of the TTC.

Image angular velocity \( \omega \) [rad \ s\(^{-1}\)] or the ventral flow has been defined by Srinivasan et al. [3] as:

\[ \omega = \frac{V}{D} \]

where \( V \) [m \ s\(^{-1}\)] is the translational velocity along which the image angular velocity is measured and \( D \) [m] is the distance from the eye to the surface generating the visual features on the retina. Image angular velocities in both image directions \( \omega_x, \omega_y \) can be defined by using \( V_x, V_y \) respectively in equation 9. It is clear that in the case of a downward looking camera the image angular velocities are the scaled lateral velocities presented as the first terms in (1) and (2).

III. OPTIC FLOW MODELLING

By careful inspection of the ego-motion equations (1) and (2), the following parameters can be defined:
a_1 = -f \left( \frac{V_x}{Z} + W_y \right) \quad a_2 = \frac{V_x}{Z} \quad a_3 = W_z \quad a_4 = \frac{W_x}{f} \quad a_5 = -\frac{W_y}{f} \quad a_6 = -f \left( \frac{V_x}{Z} - W_x \right)

which allows modelling the estimated optic flow using the ego-motion equations and the above model parameters as:

\begin{align}
  u &= a_1 + a_2 x + a_3 y + a_4 x y + a_5 x^2 \quad \text{(11)} \\
  v &= a_6 - a_3 x + a_2 y + a_5 y^2 + a_4 y^2 \quad \text{(12)}
\end{align}

If the camera focal length f is known then the angular velocities of the observer can be deduced as follows:

\begin{align}
  W_x &= f a_4 \\
  W_y &= -f a_5 \\
  W_z &= a_3 
\end{align}

The equations for TTC (T_c), lateral ventral flows (\omega_x, \omega_y), and the FOE location (x_{foe}, y_{foe}) can be found as follows:

\begin{align}
  T_c &= \frac{1}{a_2} \\
  \omega_x &= -\frac{a_1}{f} - W_y \\
  \omega_y &= -\frac{a_6}{f} + W_x \\
  x_{foe} &= \frac{x_{omega}}{a_2} \\
  y_{foe} &= \frac{y_{omega}}{a_2} 
\end{align}

Ego-motion model equations (11), (12) have six unknowns thus optic flow estimation at a minimum of three points are required to solve for the model parameters. This assumes that there is no depth variation in the scene, however with large number of optic flow measurements a minimal variation in the depth could be tolerated if the solution is found in a least square sense. The following system of equations could be written for n points:

\[
\begin{bmatrix}
  u_1 \\
  v_1 \\
  \vdots \\
  u_n \\
  v_n
\end{bmatrix} = \begin{bmatrix}
  1 & x_1 & y_1 & x_1 y_1 & x_1^2 & 0 \\
  0 & y_1 & -x_1 & y_1^2 & x_1 y_1 & 1 \\
  \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
  1 & x_n & y_n & x_n y_n & x_n^2 & 0 \\
  0 & y_n & -x_n & y_n^2 & x_n y_n & 1
\end{bmatrix} \begin{bmatrix}
  a_1 \\
  a_2 \\
  a_3 \\
  a_4 \\
  a_5 \\
  a_6
\end{bmatrix}
\]

And the values of model parameters a_1 to a_6 can be found using the least squares solution of the over-determined system defined in (15).

In addition to facilitate visual motion parameters estimation, the achieved optic flow model in a previous frame helps providing an initial guess to the optic flow estimation algorithm in the next frame by projecting the points in question using (1) and (2). By doing this both the reliability and the performance of the optic flow estimation is enhanced especially when the magnitude of optic flow becomes large due to large displacement or when the depth becomes small.

IV. RESULTS

A dynamic virtual environment is built using VRML and integrated in a simulation environment using Simulink and Simulink 3D animation toolbox. The images generated from the toolbox are (720×576) pixels and simulates a camera with (71°×49°)FoV. Optic flow measurements from generated image stream are calculated using Pyramid- dal implementation of Lucas and Kanade sparse optic flow at a maximum of 200 features chosen for best tracking using Harris corner [17] finder. Visual motion parameters are estimated and compared with ground truth values from the Simulink environment. A side-view of the simulated environment is shown in Fig. 1 where the simulated camera is carried below the aerial robot (top of Fig (1) and facing the ground. The tests are performed on an Intel Core i5 2.5 Ghz and was able to achieve a frame rate of 33 fps inclusive of the optic flow estimation.

The accuracy of the estimation is tested under two different motion profiles. The first is achieved by directly moving the camera through an axial motion with V = (0.75, 0.5, 1) [m s⁻¹] and W = (0, 0, 0.1745) [rad s⁻¹]. The theoretical vs. the visually registered values for visual motion parameters TTC, \omega_x and \omega_y are shown in Fig 2, 3, 4 respectively.

The second motion profile is achieved by controlling a helicopter platform carrying the camera to move in a sinusoidal translational and rotational motion resulting in:

Motion profile shown in Fig. 5. The theoretical vs. the visually registered values for visual motion parameters TTC, \omega_x and \omega_y are shown in Fig. 6, 7, 8 respectively.

It is clear that the method produces very good estimates in the first motion profile while the quality of the estimated degrades slightly in the second motion profile. This reduced accuracy is due to invalidating the assumption of a uniform depth values for all image points when the camera tilts. However if the camera orientation is not expected to vary significantly the achieved accuracy is suitable for the purpose of robot navigation.

![Figure 1. Side-view of the simulated environment](image-url)
In order to quantitatively measure the estimation accuracy, the root mean square error (RMSE) of the five estimated visual motion parameters against their theoretical values is calculated and shown in Table I for the two motion profiles defined above. The horizontal and vertical direction $x_h, y_h$ in degrees are included for convenience.

V. CONCLUSIONS AND FUTURE WORK

In this paper a simple closed form method for estimating visual motion parameters, namely the time-to-contact, focus of expansion, and image angular velocities from a general 6 degrees of freedom camera motion. The proposed method uses sparse optic flow estimates at arbitrary image location allowing exploiting image textures in each frame. All parameters are estimated simultaneously rather than in stages to prevent error accumulation. The method managed to accurately estimate the required parameters in real-time.
TABLE I.  ROOT MEAN SQUARE OF THE ESTIMATED PARAMETERS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Motion 1</th>
<th>Motion 2</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_e$</td>
<td>0.097</td>
<td>0.189</td>
<td>seconds</td>
</tr>
<tr>
<td>$w_x$</td>
<td>0.0075</td>
<td>0.0284</td>
<td>deg s^{-1}</td>
</tr>
<tr>
<td>$w_y$</td>
<td>0.0052</td>
<td>0.0127</td>
<td>rad s^{-1}</td>
</tr>
<tr>
<td>$\Sigma_{T_e}$</td>
<td>4.3924</td>
<td>36.2498</td>
<td>pixels</td>
</tr>
<tr>
<td>$\Sigma_{w_x}$</td>
<td>7.6814</td>
<td>16.9793</td>
<td>pixels</td>
</tr>
<tr>
<td>$\Sigma_{w_y}$</td>
<td>0.4331</td>
<td>3.5746</td>
<td>degree</td>
</tr>
<tr>
<td>$\Sigma_{h_x}$</td>
<td>0.7841</td>
<td>1.1333</td>
<td>degree</td>
</tr>
</tbody>
</table>

Future work should find ways to address degradation in estimation accuracy due to variation in depth due to multiple planar objects or slant surfaces possibly due to camera orientation without adding the complexity of resolving depth itself.

REFERENCES


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