Optical Flow Based Robot Homing

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Introduction

• Navigation of mobile robots is at the heart of today’s robotic systems. Navigation involves the creation of topological and/or metric maps by the mobile robot. Homing refers to the navigation method for returning an agent to its home position. Various sensors are used for tackling the problem such as visual, laser, and odometry. Computation cost is a main problem in navigation.

• Biology is seen as an alternative method to problems encountered by sophisticated robotic systems. Biological inspiration provides simple, yet effective solutions to those problems. The examination of biology has a twofold gain. The study of biology entails making better autonomous systems while at the same time the building up of such systems gives us an understanding of how the underlying mechanisms of a biological organism work.
Aims and Objectives

• The aim of this work is to apply vision systems to mobile robotics for the purpose of providing navigation capabilities to robotic systems.

• The objective of this research is to add to the understanding of visual-based navigation for fully autonomous mobile robots. Inspiration is drawn from biological and other studies.

• The purpose of this work is to find how a mobile robot can effectively return to its home using computationally efficient biological and other techniques for navigation.
Simulation Environment

• Vision sensors are cheap and provide a plethora of information. Other sensors, like laser range scanners have been considered mainly for obstacle avoidance.
• Simulation tools. 2D Player/Stage simulator, 3D Gazebo and breve simulator.
• Simulated devices and sensors:
  – Mobile robotic platform
  – Vision sensors
  – *Laser range finder*
Biology

• Insects (ants and honeybees) make use of:
  – Visual landmarks
  – Turn-back-and-look approach
  – *Path integration*
  – *Pheromone trail following*
  – *Searching techniques*
Biological Maps

- Use of optical flow as the only information to tackle the localization problem by constructing topological maps based on the optical flow *fingerprint* of the landmarks
- Optic flow, is not a property of landmarks like color, shape, and size, but a property of the camera motion
- A probabilistic score is inferred to localize the robot in *a priori* unknown environment. For this purpose a training algorithm has been developed
Lucas-Kanade algorithm

• In order for the optical flow algorithms to perform well some suitable images need to be chosen. Texture and corners refers to this suitability
• Such images have strong derivates and when two orthogonal derivatives are observed then this feature may be unique and good for tracking.
• In Lucas-Kanade corners are more suitable than edges for tracking.
Lucas-Kanade algorithm

- Lucas-Kanade algorithm is a *sparse optical flow* algorithm in contrast to *dense optical flow* algorithm.
- Sparse optical flow refers to an algorithm that uses local information that is derived from some small window surrounding each of the points of interest. Dense optical flow uses global information.
Lucas-Kanade algorithm

- Pyramidal Lucas-Kanade algorithm was developed to overcome the problem of large motion tracking.
Lucas-Kanade algorithm

- The optic flow algorithm of Lucas-Kanade presupposes three main criteria to produce satisfactory results
  - Brightness constancy. The brightness of a pixel does not change from frame to frame
  - Temporal persistence or small movements. The motion of the object that is tracked moves smoothly from frame to frame
  - Spatial coherence. Neighboring points of a pixel that belong to the same surface have typically similar motion, and project to nearby points on the image plane
Optical Flow

• Low computational cost aside from LK algorithm
  – Images are only captured; images are not stored or compared

• Only the properties of vectors are stored and compared
  – Mean position of vectors
  – Number of vectors
Training Algorithm

- Training algorithm consisting of 1000 observations drawn from two Gaussian distributions of two independent variables, namely distance and velocity

- Velocity (V): $\mu=4$, $\sigma=1$ (km/h)
- Distance (D): $\mu=11$, $\sigma=3$ (meters)

\[
\overline{x}, \overline{y} = \frac{1}{n} \cdot \sum_{k=1}^{n} x_k, y_k \quad n = 1000.
\]

\[
\chi_k = \sqrt{(x_k - \overline{x})^2 + (y_k - \overline{y})^2}.
\]
Training Algorithm

- Modeling distance and velocity
Training Algorithm

Log normal pdf and cdf. $\mu=2.24$, $\sigma=0.86$.

$$f_X(\delta; \mu, \sigma) = \frac{1}{\delta \sigma \sqrt{2\pi}} e^{- \frac{(\ln \delta - \mu)^2}{2\sigma^2}} \quad x > 0$$

$$F_X(\delta; \mu, \sigma) = \frac{1}{2} \text{erfc} \left[ - \frac{\ln \delta - \mu}{\sigma \sqrt{2}} \right] = \Phi \left( \frac{\ln \delta - \mu}{\sigma} \right)$$
Test Phase

- Calculate mean points for outbound and inbound journeys and infer similarity score

\[
\bar{x}_i, \bar{y}_i = \frac{1}{r} \cdot \sum_{a=1}^{r} x_a, y_a
\]

\[
\bar{x}_j, \bar{y}_j = \frac{1}{s} \cdot \sum_{b=1}^{s} x_b, y_b
\]

\[
\delta = \sqrt{(\bar{x}_i - \bar{x}_j)^2 + (\bar{y}_i - \bar{y}_j)^2}
\]

\[
P = 1 - P_\delta
\]

\[
PT = P\left(\frac{\min_i}{\max_j}\right)
\]
Test Phase

• Reference snapshot
  Distance: 11 meters
  Velocity: 4 km/h
Test Phase

Time = t, D = 8m, V = 4km/h

Time = t + 2\Delta t

Landmarks: 1, Gr elements: 234, Bl elements: 308, Deviation: 7.66, Probability: 45.01%

Landmarks: 1, Gr elements: 234, Bl elements: 343, Deviation: 25.32, Probability: 8.37%
Test Phase

Time = t, D = 11m, V = 5km/h

Time = t + 2Δt

Landmarks: 1, Gr elements: 234, El elements: 227, Deviation: 2.18, Probability: 92.71%

Landmarks: 1, Gr elements: 234, El elements: 237, Deviation: 13.42, Probability: 33.27%
Test Phase

Time=$t$, D=$8m$, V=$5km/h$

Time=$t+2\Delta t$
Test Phase

Time = $t$, D = 11m, V = 4km/h

Time = $t$, D = 8m, V = 5km/h
Test Phase

Time = \( t \), \( D = 11m \), \( V = 4km/h \)
Distance vs Velocity

- The following tables show that distance influences more the similarity score than velocity.

### Optical Flow Performance at 8m and 4km/h

<table>
<thead>
<tr>
<th>Time t</th>
<th>No of vectors</th>
<th>Deviation</th>
<th>Probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t + 3\Delta t$</td>
<td>394</td>
<td>24.58</td>
<td>7.71</td>
</tr>
<tr>
<td>$t + 2\Delta t$</td>
<td>343</td>
<td>25.32</td>
<td>8.37</td>
</tr>
<tr>
<td>$t - 2\Delta t$</td>
<td>294</td>
<td>14.33</td>
<td>24.63</td>
</tr>
<tr>
<td>$t + \Delta t$</td>
<td>395</td>
<td>10.67</td>
<td>26.01</td>
</tr>
<tr>
<td>$t - \Delta t$</td>
<td>306</td>
<td>8.07</td>
<td>43.50</td>
</tr>
<tr>
<td>$t$</td>
<td>308</td>
<td>7.66</td>
<td>45.01</td>
</tr>
</tbody>
</table>

### Optical Flow Performance at 11m and 5km/h

<table>
<thead>
<tr>
<th>Time t</th>
<th>No of vectors</th>
<th>Deviation</th>
<th>Probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t - 3\Delta t$</td>
<td>265</td>
<td>40.23</td>
<td>3.92</td>
</tr>
<tr>
<td>$t - 2\Delta t$</td>
<td>273</td>
<td>30.28</td>
<td>7.31</td>
</tr>
<tr>
<td>$t + 2\Delta t$</td>
<td>237</td>
<td>13.42</td>
<td>33.27</td>
</tr>
<tr>
<td>$t - \Delta t$</td>
<td>203</td>
<td>9.52</td>
<td>42.70</td>
</tr>
<tr>
<td>$t + \Delta t$</td>
<td>219</td>
<td>5.21</td>
<td>70.49</td>
</tr>
<tr>
<td>$t$</td>
<td>227</td>
<td>2.18</td>
<td>92.71</td>
</tr>
</tbody>
</table>

### Optical Flow Performance at 8m and 5km/h

<table>
<thead>
<tr>
<th>Time t</th>
<th>No of vectors</th>
<th>Deviation</th>
<th>Probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t + 4\Delta t$</td>
<td>223</td>
<td>47.05</td>
<td>2.83</td>
</tr>
<tr>
<td>$t + 3\Delta t$</td>
<td>198</td>
<td>43.97</td>
<td>5.60</td>
</tr>
<tr>
<td>$t + 2\Delta t$</td>
<td>205</td>
<td>27.63</td>
<td>9.04</td>
</tr>
<tr>
<td>$t - \Delta t$</td>
<td>254</td>
<td>21.64</td>
<td>15.11</td>
</tr>
<tr>
<td>$t + \Delta t$</td>
<td>169</td>
<td>14.18</td>
<td>22.67</td>
</tr>
<tr>
<td>$t$</td>
<td>174</td>
<td>11.33</td>
<td>30.61</td>
</tr>
</tbody>
</table>
Distance Estimation

- Optical flow method for depth estimation
  - Regression analysis and has been used to estimate the distance between the robot and an object

- A second strategy for estimating depth that utilizes a least squared approach
Depth Estimation

• The regression formula that expresses the distance, $D$, between a landmark and the robot based on the observed length, $len$, of the optical flow vectors is given by the following equation

$$\ln D_i = a + b \cdot len_i + \varepsilon_i$$
Depth Estimation

- The purpose is to estimate depth using a single camera
Depth Estimation

- Every snapshot represents a linear equation

\[
L \in \Omega_1 = \{ h \in \mathbb{R}^2 \mid \frac{(v_1 - r_1)^T}{\alpha_1} h = \frac{v_1^T \cdot r_1 - \|r_1\|^2}{\beta_1} \}
\]

\[
L \in \Omega_2 = \{ h \in \mathbb{R}^2 \mid \frac{(v_2 - r_2)^T}{\alpha_2} h = \frac{v_2^T \cdot r_2 - \|r_2\|^2}{\beta_2} \}
\]

\[
h \in \arg\min \sum_{i=1}^{n} (h\alpha_i - \beta_i + \epsilon_i)^2
\]

\[
\left( \sum_{i=1}^{n} \alpha_i \alpha_i^T + \epsilon_i \right) h = \left( \sum_{i=1}^{n} \alpha_i \beta_i \right)
\]

\[
h = C^{-1} \gamma
\]
Depth Estimation

- Comparison between actual and estimated distance (4m, 8m)
Depth Estimation

• Comparison between actual and estimated distance (12m, 16m)
Depth Estimation

• Performance of least squares and optical flow methods

<table>
<thead>
<tr>
<th>Snapshots $n$</th>
<th>$R^2 (\epsilon_i \pm 1^\circ)$</th>
<th>$R^2 (\epsilon_i \pm 3^\circ)$</th>
<th>$R^2 (\epsilon_i \pm 5^\circ)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.971</td>
<td>0.137</td>
<td>0.000</td>
</tr>
<tr>
<td>6</td>
<td>0.991</td>
<td>0.722</td>
<td>0.000</td>
</tr>
<tr>
<td>8</td>
<td>0.996</td>
<td>0.883</td>
<td>0.336</td>
</tr>
<tr>
<td>10</td>
<td>0.998</td>
<td>0.940</td>
<td>0.649</td>
</tr>
<tr>
<td>12</td>
<td>0.999</td>
<td>0.967</td>
<td>0.801</td>
</tr>
<tr>
<td>14</td>
<td>0.999</td>
<td>0.979</td>
<td>0.881</td>
</tr>
<tr>
<td>16</td>
<td>1.000</td>
<td>0.987</td>
<td>0.915</td>
</tr>
<tr>
<td>18</td>
<td>1.000</td>
<td>0.991</td>
<td>0.944</td>
</tr>
<tr>
<td>20</td>
<td>1.000</td>
<td>0.993</td>
<td>0.959</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Velocity $e$ (km/h)</th>
<th>Constant $a$</th>
<th>Coefficient $b$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$2 &lt; e &lt; 6$</td>
<td>2.96</td>
<td>-0.075</td>
<td>0.6029</td>
</tr>
<tr>
<td>$2 &lt; e &lt; 5$</td>
<td>3.03</td>
<td>-0.09</td>
<td>0.6483</td>
</tr>
<tr>
<td>$2 &lt; e &lt; 4$</td>
<td>3.08</td>
<td>-0.11</td>
<td>0.7569</td>
</tr>
<tr>
<td>$2 &lt; e &lt; 3$</td>
<td>3.1</td>
<td>-0.143</td>
<td>0.8052</td>
</tr>
</tbody>
</table>
Thank you

Questions?