Marker-Based Mapping and Localization for Autonomous Valet Parking

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What is AVP?

Traditional valet parking

Auto valet parking
Benefits & Challenges

• Driver-friendly
• Enable high density parking
  • (1.6 million parking spaces for 4.37 million vehicles in Beijing for 2014)
• Reduce accidents caused by human errors during parking
  • (40% Accidents occur during parking related maneuvers)

• No GPS signals available
• Vehicle movements will change the appearance of the same place
• Illumination condition is complicated in such scenes
Related Works

- Geometric SLAM Methods
  - **ORB_SLAM2**
    (IEEE Transaction on Robotics 2017)
  - **VINS MONO**
    (IEEE Transaction on Robotics 2018)

- Semantic SLAM Methods
  - **Detect ground parking slots**
    (IV 2018)
  - **AVP-SLAM**
    (IROS 2020)

- Feature-based maps lack long-time stability
- Resource-demanding
- Ground information may suffer from occlusion or wearing
Algorithm Pipeline

Monocular image → Visual Marker detection → Local Mapping With Marker → Loop detection → Global Marker Map

Mapping

Steering angle → Odometry → Visual localization → Particle Filter → 6-DoF pose

Localization

Wheel encoder
Mapping Algorithms

Local Mapping

Monocular Image → Pre-Processing ORB and Markers → Track frame/local map → Need New KeyFrame?

Landmarks Culling, Creation → Local BA with vehicle model → KeyFrame Culling

Map
- MapPoints
- Covisibility Graph
- Spaping Tree
- Markers

Place Recognition
- Visual Vocabulary
- Recognition Database

Loop Detection → Loop Correction

Tracking
Mapping Algorithms

• Scale Recovery From Visual Fiducial Markers

1. Get the side length of the printed markers
2. According to the hypothetical 3D marker coordinate, get the corresponding corner point coordinate.
3. Extract markers from monocular image
4. Solve the PnP problem to get the relative pose of marker
5. Given the poses of the same marker in two images, we can recover the scale of monocular slam

\[ R_{CW}^{k+1} R_{CM}^{k+1} p_{M,C}^{k+1} - R_{CW}^{k} R_{CM}^{k} p_{M,C}^{k} = s(p_{WC}^{k+1} - p_{WC}^{k}) \]
• Pose Optimization with Vehicle Odometry Constraints

1. Fuse wheel speed and steering angle to form vehicle odometry
2. Add the vehicle odometry constraint edge to pose optimization
Localization Algorithms

- Structure

- Initialization
  - Data Association (Using Marker ID)
  - Coordinate Transform
    \[
    \begin{bmatrix}
    x_0 \\
    y_0 \\
    \theta_0
    \end{bmatrix}
    =
    \begin{bmatrix}
    x_k - x' \cos \theta' + y' \sin \theta' \\
    y_k - x' \sin \theta' + y' \cos \theta' \\
    \theta_k - \theta'
    \end{bmatrix}
    \]
  - Distribute Particles
    \[
    \begin{bmatrix}
    x_n \\
    y_n \\
    \theta_n
    \end{bmatrix}
    =
    \begin{bmatrix}
    N(x_0, std_{x}^2) \\
    N(y_0, std_{y}^2) \\
    N(\theta_0, std_{\theta}^2)
    \end{bmatrix}
    \]
Localization Algorithms

- **Motion Update**

\[ p(X_t|z_t, u_t, X_{t-1}, m) = p(X_t|u_t, X_{t-1}) \]

- **Observation Update**

\[ p(X_t|z_t, u_t, \hat{X}_t, m) = p(X_t|z_t, m, \hat{X}_t) \]

- **Marker Filtering**

- **Data Association & Coordinate Transform**

\[ \begin{bmatrix}
  x_{ob-\text{map}} \\
  y_{ob-\text{map}} \\
  \theta_{ob-\text{map}}
\end{bmatrix} = \begin{bmatrix}
  x_{ob} \cos \theta_n - y_{ob} \sin \theta_n + x_n \\
  x_{ob} \sin \theta_n + y_{ob} \cos \theta_n + y_n \\
  \theta_{ob} + \theta_n
\end{bmatrix} \]
Localization Algorithms

- Observation Update
  - Update Particle Weights
    $$w_n = \frac{e^{-\left(\left(\frac{(x_{ob\_map} - x_{ob})^2}{\sigma_x^2}\right) + \left(\frac{(y_{ob\_map} - y_{ob})^2}{\sigma_y^2}\right)\right)}}{2\pi \sigma_x \sigma_y}$$
  - Resampling
    - No resampling while stationary
  - Output Vehicle Pose
    - Get average particle state rather than highest weighted

- Visualization
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Experiments

• Mapping Metric Evaluation

Environment:
- Underground garage about $500m^2$
- Marker size is 0.552m
- Average interval between markers is 8m
- Total trajectory length is 143m

Results:
- RMSE is 0.438m
- NESS is 0.306%
Experiments

- Localization Accuracy Evaluation

<table>
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<th>Error(m)</th>
<th>Mean</th>
<th>Max</th>
<th>Min</th>
<th>Std</th>
<th>Median</th>
<th>RMSE</th>
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<td>Experiment 1</td>
<td>0.301586</td>
<td>0.775068</td>
<td>0.015272</td>
<td>0.171292</td>
<td>0.259017</td>
<td>0.346836</td>
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<td>Experiment 2</td>
<td>0.263982</td>
<td>0.686745</td>
<td>0.024782</td>
<td>0.157513</td>
<td>0.225755</td>
<td>0.307403</td>
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</tbody>
</table>
Experiments

• Computational Resources

<table>
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<th></th>
<th>CPU occupation</th>
<th>Memory used [MB]</th>
<th>Frequency [Hz]</th>
</tr>
</thead>
<tbody>
<tr>
<td>i7 laptop</td>
<td>14%</td>
<td>500</td>
<td>100</td>
</tr>
<tr>
<td>A53 embedded</td>
<td>25%</td>
<td>510</td>
<td>100</td>
</tr>
</tbody>
</table>

• System Robustness

• False matches due to environment appearance changes

• Marker detections not affected
Conclusions

• Pros

  • Long-term usable map & High environmental robustness
  • Low computational resource consumption

• Cons

  • Limited scene of application
THANK YOU