Robust Multi-Target Tracking in Outdoor Traffic Scenarios via Persistence Topology based Robust Motion Segmentation

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Vision system for self-driving car
Pipeline

- Stereo Disparity Map
- Robust Tracking
- Occupancy Grid Computation
- Persistence Analysis
- Robust Motion Segmentation
- Occupancy Grid Alignment
Stereo Disparity Map

- We Use Semi Global Block Matching (SGBM) to compute the disparity map. Higher value means closer to the camera.
Stereo Disparity Map

- UV disparity map
Ground Segmentation

- Fit a line or plane in V-diaprity map.

V disparity map
Occupancy Grid Computation

Pipeline

- Stereo Disparity Map
- Robust Tracking
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- Robust Motion Segmentation
- Persistence Analysis
- Occupancy Grid Alignment
Topological Persistence

\[ \tau = 0.2 \quad \tau = 0.24 \quad \tau = 0.25 \quad \tau = 0.49 \quad \tau = 0.64 \]
Persistence Diagram

- Apply a threshold to persistence diagram to avoid noise
Persistence Diagram

- Regions with high enough persistence are the result regions.
Robust Segmentation

• Segmentation by threshold method

• Segmentation by persistence method
Occupancy Grid Alignment

• Compute the rotation (R) and translation (T) motion between successive images using SIFT

• Use the homograph information to accumulate the occupancy map by a Bayesian filter approach

Three successive occupancy maps

Accumulate occupancy map
Motion Segmentation

• In the accumulated occupancy grid, the regions with higher probability represent the static object.

• The region with low probability are the objects in motion.
Pipeline

Stereo Disparity Map → Occupancy Grid Computation → Persistence Analysis → Robust Motion Segmentation → Occupancy Grid Alignment → Robust Tracking
Robust Tracking


Robust Tracking

• Solve a maximize a posteriori probability problem

\[
T_r = \arg\max_T P(T|O) = \arg\max_T P(O|T)P(T)
\]

\[
T_r = \arg\max_T \prod_j P(T_j) \prod_i P(o_i|T)
\]

\[
T_r = \arg\min_T \left( \sum_j \log(P(T_j)) + \sum_i \log(P(o_i|T)) \right)
\]

\[
P(T_j) = P_e^2 P(o_{j1}, o_{j2}) P(o_{j2}, o_{j3}) \ldots P(o_{j_{n-1}}, o_{jn})
\]
Robust Tracking

\[ T_r = \arg\min_T \left( \sum_j \log(P(T_j)) + \sum_i \log(P(o_i|T)) \right) \]

\[ T_r = \arg\min_T \left( \sum_j C_e + \sum_i C_i + \sum_{m,n} C_{m,n} \right) \]

\[ C_e = -\log(P_e^2) \]

\[ C_i = -\log(P(o_i|T)) \]

\[ C_{m,n} = -\log(P(o_m), P(o_n)) \]
Robust Tracking
Experiment

• Implemented in MATLAB

• Use KITTI dataset
  - A: 200 frames represent inner city
  - B: 120 frames represent residential traffic
Experiment

• Tracking results over 10 consecutive frames
Evaluation

- Motion segmentation

**Precision** = correct matches / total groundtruth objects

**Recall** = correct matches / output objects.

**FA/Frm** = No. of false alarms per frame.

<table>
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<tr>
<th>Dataset</th>
<th>Precision</th>
<th>Recall</th>
<th>FA/Frm</th>
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<td>0.96</td>
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Evaluation

Persistence - Average Length = 38.1

Thresholding - Average Length = 21.2
Evaluation

- Tracking

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<th>GT</th>
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<th>MOTA</th>
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</table>

Number of groundtruth trajectories
Thanks!