Object Scene Flow for Autonomous Vehicles

Moritz Menze1, Andreas Geiger2
1Leibniz Universität Hannover, 2MPI for Intelligent Systems, Tübingen

We propose a novel model and dataset for 3D scene flow estimation with an application to autonomous driving. As outdoor scenes often decompose into a small number of independently moving objects, we represent each element in the scene by its rigid motion parameters and each superpixel by a 3D plane and an index to the corresponding object. This minimal representation increases robustness and is formulated in a discrete-continuous CRF. Our model intrinsically segments the scene into its constituting dynamic components. We demonstrate the performance of our model on existing benchmarks and a novel realistic dataset with scene flow ground truth. We obtain this dataset by annotating 400 dynamic scenes from the KITTI raw data collection using 3D CAD models for all vehicles in motion. Our experiments reveal novel challenges which cannot be handled by existing methods.

Abstract

Data Term

The data term $\varphi$ consists of pairwise potentials which are evaluated for 3 pairs of images (see figure below)

\[
\varphi(u, v, o, o', j) = \delta_{ij}(o, o') \cdot D_j(u, v)
\]

where the leaves are the selected object.

To compute $D_j(u, v)$ we leverage:

- Dense Census features
- Sparse optical flow from feature matches
- SGM disparity maps for both rectified pairs

Results on the "Sphere" sequence

Quantitative Results

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE Disparity</th>
<th>RMSE 2D Flow</th>
</tr>
</thead>
<tbody>
<tr>
<td>SGM [3]</td>
<td>0.75</td>
<td>0.55</td>
</tr>
<tr>
<td>Sun [6]</td>
<td>0.90</td>
<td>0.56</td>
</tr>
<tr>
<td>GCSF [2]</td>
<td>0.84</td>
<td>0.57</td>
</tr>
<tr>
<td>Huguet [5]</td>
<td>0.87</td>
<td>0.60</td>
</tr>
<tr>
<td>SGM + Sphere Flow [4]</td>
<td>0.80</td>
<td>0.56</td>
</tr>
<tr>
<td>GCSF + Sun [6]</td>
<td>0.85</td>
<td>0.57</td>
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<tr>
<td>GCSF + PRSF [8]</td>
<td>0.82</td>
<td>0.57</td>
</tr>
<tr>
<td>GCSF + SGM [3]</td>
<td>0.83</td>
<td>0.57</td>
</tr>
</tbody>
</table>

We encourage the orientation of neighboring planes to be similar by evaluating the differences in plane normals $n(o, n)$:

\[
\psi_2(n(o), n(n')) = \sum_{ij} \theta(\psi_1(o_i, n_i), \psi_1(o_j, n_j))
\]

Qualitative Results

Each silhouette shows from top-to-bottom: disparity and optical flow ground truth in the reference frame, the disparity map (D1) and optical flow map (F) estimated by our algorithm, and the motion error images using the color scheme depicted in the legend. The four scenes below the horizontal line are future cases.

References


Results on the "Sphere" sequence

Illustration of our results for the synthetic "Sphere" sequence [5]. Typical to motion right. Top row: left image of the first frame, our first disparity map, the obtained segmentation into its constituting dynamic components. We encourage the orientation of neighboring planes to be similar by enforcing an orientation-sensitive Potts model. The motion error images are depicted using the color scheme depicted in the legend.

Dataset

We propose a novel realistic scene flow dataset which includes dynamic objects

We annotated 200 training and 200 test scenes based on KITTI raw data

The static background of the scenes is recovered from laser scanner data by removing all dynamic objects and compensating for the vehicle's ego-motion

With weights $\delta_{ij}$ controlling the individual terms:

- Regularization of depth is achieved by penalizing differences in disparity at shared boundary pixels ($\delta_{ij}$)
- We encourage the orientation of neighboring planes to be similar by evaluating the differences in plane normals $n(o, n')$:

\[
\psi_2(n(o), n(n')) = \sum_{ij} \theta(\psi_1(o_i, n_i), \psi_1(o_j, n_j))
\]

Inference

- We use an object-based particle filter to jointly infer shape and motion parameters with TRHS for the inner loop.
- Particles are drawn from normal distributions around the current MAP solution and from neighboring superpixels.

Contact Information

http://cvlab.cs.uni-hannover.de/objectsceneflow

Andreas Geiger, Andreas Geiger, http://cvlab.cs.uni-hannover.de/objectsceneflow.png

1 Leibniz Universität Hannover, 2MPI for Intelligent Systems, Tübingen