Learning non-rigid surface reconstruction from spatio-temporal image patches

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Learning non-rigid surface reconstruction from spatio-temporal image patches

- **Input**: a video sequence of a moving object

- **Output**: XYZ-coordinates of the points

- **Typical solutions involve**:
  1. Tracking feature points across frames + NRSfM
  2. Exploiting assumptions on camera, shape of the object, trajectories etc.

  ...ill-posed, mathematically challenging
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- **Motivation**: Circumvent difficult mathematical challenges and avoid point tracking

- **Idea**: Train a network to infer shape directly from the video sequence…but how?

- Synthetically generate database of short movie clips of realistically deforming surfaces, and their corresponding depth maps.

- Divide the video into patches, estimate depth, combine together
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**Assumptions:**

1. Static and orthographic camera (=> video depth estimation)

2. Non-negligible deformation of the object across time

3. Locally, the 4D structure of the object can be approximated with a parametric model
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Orthographic camera:

• Easier to train than perspective camera, but...

• PROBLEM: linear ambiguity (GBR transformation)

Example of generalized bas-relief ambiguity. From left to right, two versions of the same surface, of which the second one is a GBR transformed version of the first one, and their corresponding views from an orthographic camera located at (0, 0, 1). The GBR transformation changes the orientation of the surface normals, which in turn slightly changes the albedo pattern of the surface. However, the second image can be mistakenly interpreted as its non-transformed version rendered with the same texture with slightly modulated pixel intensities.
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Orthographic camera:

- Easier to train than perspective camera, but...

- **PROBLEM**: linear ambiguity (GBR transformation)

- **Proposed solution**: represent surfaces with GBR-invariants

The normalized Hessian of a depth map $z$ is a complete differential invariant to generalized bas-relief transformations.
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Network architecture (based on 3D U-net)
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GBR-invariant loss function

\[
\frac{\nabla^2 z}{\|\nabla^2 z\|_F} = \frac{1}{\sqrt{z_{xx}^2 + z_{xy}^2 + z_{yx}^2 + z_{yy}^2}} \begin{pmatrix} z_{xx} & z_{xy} \\ z_{yx} & z_{yy} \end{pmatrix}
\]

- Each pixel of the GBR-invariant depth map has **two degrees of freedom** (…can be seen as points on the unit sphere in 3D space)

- Euclidean distance corresponds to chordal distance between points on the sphere

Visualized in Lab color space
Results

- Synthetic data
- Different motion parameters than in training
- Comparison with two state-of-the-art NRSfM methods

CSF2


KSTA


Ground truth

Ours

CSF2

KSTA
Results (real data)

Kinect RGB sequence

Kinect Depth maps

CSF2

Ours
More results...
## Quantitative results

### Synthetically generated sequences

<table>
<thead>
<tr>
<th></th>
<th>Ours</th>
<th>CSF2</th>
<th>KSTA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MAE</strong></td>
<td>0.5907 ± 0.4536</td>
<td>0.8746 ± 0.6372</td>
<td>0.8738 ± 0.6369</td>
</tr>
</tbody>
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Average and standard deviation of *spatially normalized MAE* calculated from 1000 videos

### Kinect sequences

<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td><strong>MAE</strong></td>
<td>3.7 mm</td>
<td>4.6 mm</td>
<td>4.3 mm</td>
</tr>
</tbody>
</table>

Average *MAE* calculated from two Kinect sequences