Shrink Wrapping Small Objects
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INTRODUCTION

- **Problem:** Scanning and modelling small objects using RGBD sensors such as the Kinect.
- **Goal:** To build shape and appearance models using geometric flow based approaches for surface modelling.
- We register the point clouds by recovering the rigid transformation between successive pairs in a sequence of views, and then demonstrate the utility of surface evolution for shrink wrapping the result using weighted geometric flows.

DATA ACQUISITION

- In our experiments we use a PrimeSense Carmine 1.09, which is a high resolution short range RGBD sensor suited to capture small objects.
- The input is in the form of 3D Point clouds with xyz point values and RGB color values.

SURFACE EVOLUTION

- The level set surface is set up as a bounding box containing the data.
- \( \phi \) is an unsigned outward distance function to the data which plays the role of weighting the flow.

SURFACE EVOLUTION

- A surface \( \delta \) moves in the direction of its inward normal \( \vec{n} \) with speed \( F \) as
  \[
  \frac{\partial \delta}{\partial t} = F \vec{n}
  \]
- The level set form of the weighted gradient flow is,
  \[
  \frac{\partial \Psi}{\partial t} + F \vec{n} \cdot \nabla \Psi = 0
  \]
- To compute the gradient of \( \Psi \) in the doublet we use an upwinding scheme,
  \[
  \Psi_{i+1} = \Psi_i + \Delta t \left( \max(\Psi_{i+1}(x),0) F^+ + \min(\Psi_{i+1}(x),0) F^- \right)
  \]
- Here \( D^+ \) and \( D^- \) are forward and backward finite differences.

Algorithm 1: Level Set Surface Evolution.
for each iteration \( t \) do
  Estimate the "dir" term.
  for each voxel \( i,j,k \) do
    if \( \phi(i,j,k) \) is threshold then
      speedTerm = \( F \vec{n} \cdot \nabla \Psi \)
    else
      speedTerm = \( F \vec{n} \cdot \nabla \Psi \)
    end
  end
  Update equation:
  \[
  \Psi_{i+1} = \Psi_i + \Delta t \cdot \text{speedTerm}
  \]
end

RESULTS

- Top row: Point clouds, middle row: results of our reconstruction, bottom row: distance error in voxel units.
- The results in the middle row are obtained after a few iterations of mean curvature smoothing as a post processing step.
- The results in the bottom row show the distance of each point on the shrink wrapped surface to the closest point on the point cloud in voxel units, as explained by the color bars.
- A quantitative summary of these results for the various models is shown in the table below.

<table>
<thead>
<tr>
<th>No Of Views</th>
<th>Object</th>
<th>Dimensions (voxels)</th>
<th>Avg. Distance (voxels)</th>
<th>( \sigma )</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>Horse</td>
<td>244 \times 193 \times 160</td>
<td>4.4171</td>
<td>4.0038</td>
</tr>
<tr>
<td>25</td>
<td>Humanoid</td>
<td>264 \times 286 \times 97</td>
<td>6.4073</td>
<td>5.8649</td>
</tr>
<tr>
<td>30</td>
<td>Dinosaur</td>
<td>280 \times 267 \times 144</td>
<td>5.9817</td>
<td>5.7692</td>
</tr>
<tr>
<td>39</td>
<td>Human Head</td>
<td>190 \times 236 \times 288</td>
<td>10.1955</td>
<td>9.7089</td>
</tr>
</tbody>
</table>

CONCLUSION

- We have demonstrated the use of weighted geometric flows to reconstruct surfaces using registered point clouds of 3D data obtained from RGBD sensors.
- Our method is better able to capture surface shape including its curvature and is robust to holes in the point cloud data.
- We are able to create watertight models of objects even when some data is missing.
- We obtain good estimates of surface normals and mean curvature.
- Limitation: We assume that the point clouds are dense and outliers have been eliminated.

REFERENCES


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