Robust Region Detection via Consensus Segmentation of Deformable Shapes

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Overview

1 Introduction
   • Motivation
   • Related Work

2 Approach
   • Algorithm Outline
   • Ensemble of Segmentation
     • Enlightenment from Heat Diffusion
     • Global Point Signature
     • Ensemble of Segmentations
   • Consensus Segmentation

3 Discussion
   • Experiment Results
   • Repeatability and Sensitivity
   • Performance

4 Conclusion
Motivation

1. Features are important
2. Region & point features
3. Split first
4. * invariant and efficient

The algorithm, data and figures are cited from [Rodolà et al]
Related work

- Randomized cuts on meshes
- Component tree on meshes
- Detect features at coarser level
- et al
Algorithm Outline

Ensemble of Segmentation

Consensus Segmentation
Algorithm Outline Example

Ensemble of segmentations

Consensus segmentation
How to measure Nodes of a Shape

Heat Diffusion Equation contains both relative coordinates of nodes and difference among neighborhood. It may help. Heat Diffusion Equation:

\[ \Delta_M u = \frac{\delta}{\delta t} u \]

Eigenfunction of Laplacian:

\[ \Delta_M \Phi_i = \lambda_i \Phi_i \]

Image from http://geometry.stanford.edu/member/maks/
Eigenfunctions of Laplacian on 3D Shape
Global Point Signature (GPS)

- GPS of a point \( g(p) = \left( \frac{\Phi_1(p)}{\sqrt{\lambda_1}} \frac{\Phi_2(p)}{\sqrt{\lambda_2}} \ldots \right)^T \)
- where \( \Phi_i \) and \( \lambda_i \) are eigenfunctions and values of Laplacian of shape \( \Delta_M \Phi_i = \lambda_i \Phi_i \)
- \( G(p, q) = \langle g(p), g(q) \rangle \) measures the degree of coupling of points \( p \) and \( q \) (commute time kernel)
Ensemble

**Denotation**

\( n \) : \# of points

\( m \) : \# of segmentations

\( k_u \) : \# of segments
Building Ensemble

- Clustering
- If $k$-means clustering, then minimize

$$w(C) = \frac{1}{n} \sum_l \sum C(g(p_i)) \|g(p_i) - c_l\|^2 d(a(p_i))$$

Ensemble as current Result

But a more general segmentation is needed.
Consensus segmentation relying on aggregate statistics is more stable.

Build a segmentation that is similar to all segmentation by penalizing different labeling.

Distance equation $d^2(x, z) = \sum w_{ij} (\mathbb{T}_{x_i=x_j} - \mathbb{T}_{z_i=z_j})^2$, $\mathbb{T}_p$ is 1 if $p$ is true, otherwise 0.

$x^* \in \arg\min_{x \in [k]^n} \sum_u d(E_{u^*}, x)$

$x^*$ is optimal segmentation, $E_{u^*}$ is the label of all nodes in $u$th segmentation.
Further Explanation of $E$ and $x$

- $x^* \in \text{argmin}_{x \in [k]^n} \sum_u d(E_{u^*}, x)$

- Ensemble Matrix $E = \begin{pmatrix} E_1^* \\ E_2^* \\ \vdots \\ E_m^* \end{pmatrix} = \begin{pmatrix} E_{11} & E_{12} & \cdots & E_{1n} \\ E_{21} & E_{22} & \cdots & E_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ E_{m1} & E_{m2} & \cdots & E_{mn} \end{pmatrix}$

- Consensus segmentation $x^* = (x_{1}^* \ x_{2}^* \ \cdots \ x_{n}^*)^T$
Curse of Size

There might be over 10k or even more node in a shape, Ensemble can be super huge
Base Segments

Rebuild Ensemble by merging points that always clustered in same way

\[
\begin{bmatrix}
1 & 2 \\
1 & 2 \\
1 & 2 \\
2 & 3 \\
\end{bmatrix} \rightarrow \begin{bmatrix}
1 \\
1 \\
1 \\
2 \\
\end{bmatrix}
\]

For example

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Deformable Shapes Segmentation
16. April 2015 16 / 28
Instead of segmentation of nodes, now segmentation of base segments
Algorithm with Base Segments

Ensemble $E_{mn}$

Base Segments $F_{mn'}$

Consensus $x^* \in \arg\min_{x \in [k]^{n'}} \sum_u d(F_{u*}, x)$
Experiment Results: Deformations

Consensus segmentations of original and transformed shapes
Experiment Results: different Objects

Consensus segmentations of different shapes
Repeatability

Sensitivity w.r.t number of segmentations

Overlap vs. Repeatability (%) for different numbers of segmentations (m=3, m=5, m=10, m=25, m=50, m=75).
Terms in Repeatability Analysis

Overlap

Ratio of intersection to union of original shape and de-transformed shape
\[
\sigma(N, M) = \frac{A(N \cap f^{-1}(M))}{A(N \cup f^{-1}(M))}
\]

Repeatability

Percentage of regions detected in both shapes having overlap over \( \sigma \)

\( m \)

\( m \) is the number of segmentations in ensemble, assigned by user

Fixed parameters

Number of segments \( k_u = 10 \)
Maximal number of consensus segments \( k = 5 \)
With less dense Nodes

Original data (52k nodes), 20%, 10%, 2% sampling
### Repeatability to Number of Eigenfunctions

<table>
<thead>
<tr>
<th>num eigenfunc</th>
<th>15</th>
<th>50</th>
<th>100</th>
<th>200</th>
</tr>
</thead>
<tbody>
<tr>
<td>overlap 0.5</td>
<td>96.47</td>
<td>97.45</td>
<td>97.97</td>
<td>98.44</td>
</tr>
<tr>
<td>overlap 0.7</td>
<td>84.96</td>
<td>90.34</td>
<td>92.82</td>
<td>95.31</td>
</tr>
<tr>
<td>overlap 0.9</td>
<td>71.35</td>
<td>79.56</td>
<td>83.53</td>
<td>85.23</td>
</tr>
</tbody>
</table>

*Tabelle: Repeatability w.r.t overlap and $\#\Phi$*
### Performance

<table>
<thead>
<tr>
<th>m</th>
<th>10</th>
<th>25</th>
<th>50</th>
<th>75</th>
</tr>
</thead>
<tbody>
<tr>
<td>build $E$</td>
<td>1.94</td>
<td>4.64</td>
<td>9.24</td>
<td>14.05</td>
</tr>
<tr>
<td>get consensus</td>
<td>0.02</td>
<td>0.12</td>
<td>0.32</td>
<td>0.76</td>
</tr>
</tbody>
</table>

**Table**: average time of comp(s) on shape with 10k nodes

Ensemble building is in Matlab with standard $k$-means clustering, consensus written in C++. Intel Core i7, 4 cores, 8GB RAM.

**Parameters**: $k_u = 10$, $k = 5$, number of eigenfunctions is 50
Conclusion

In this paper a robust region-based 3D shape segmenter is proposed. The core idea is around consensus clustering from a set of segmentations. Optimization of ensemble with base segments is indicated. The robustness of this algorithm is shown by application on 3D shapes with/without deformation.
E. Rodolà, S. Rota Bulò, D. Cremers (2014)
Robust Region Detection via Consensus Segmentation of Deformable Shapes
*Eurographics Symposium Geometry Processing; Volume 33(2014), Number 5.*
The End

Thank you