Surface Segmentation of Under-sampled Meshes

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6 Nov 2001

Outline

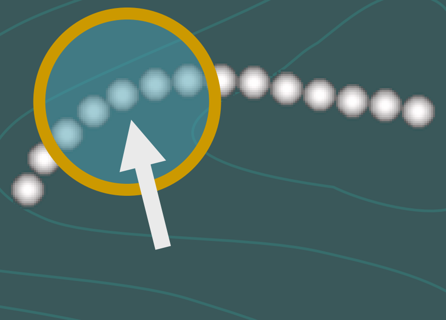
- Motivation for using segmentation
- Initial foray: Regions of constant curvature
- Normalized cuts review
- Our affinity measure
- Future work

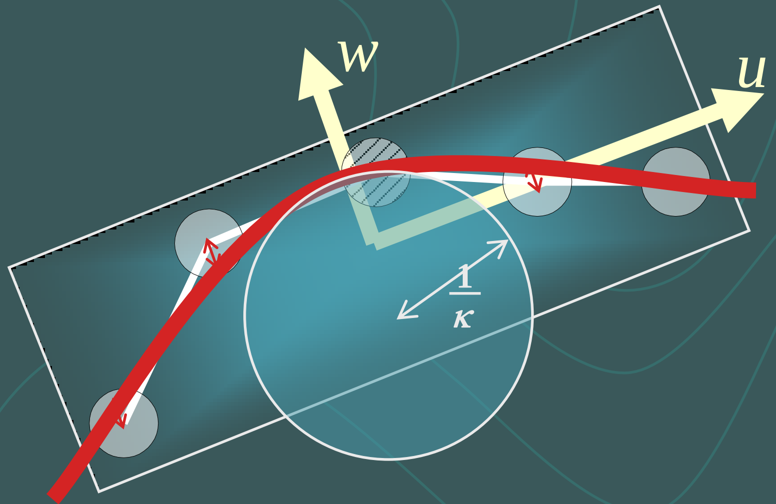
Motivation for Using Segmentation

- Project objective
  - Detecting and **recognizing** military and civilian vehicles in forested areas using range data
- Assumptions
  - Frequent non-sampling of entire vehicle “faces”
  - Data near crease edges will be highly under-sampled
- Why segmentation
  - Exploits assumption that we will tend to see large portions of faces if we see much of it at all
  - Takes the focus away from the crease edges
  - Does not rely on seeing the entire surface

Regions of Constant Curvature

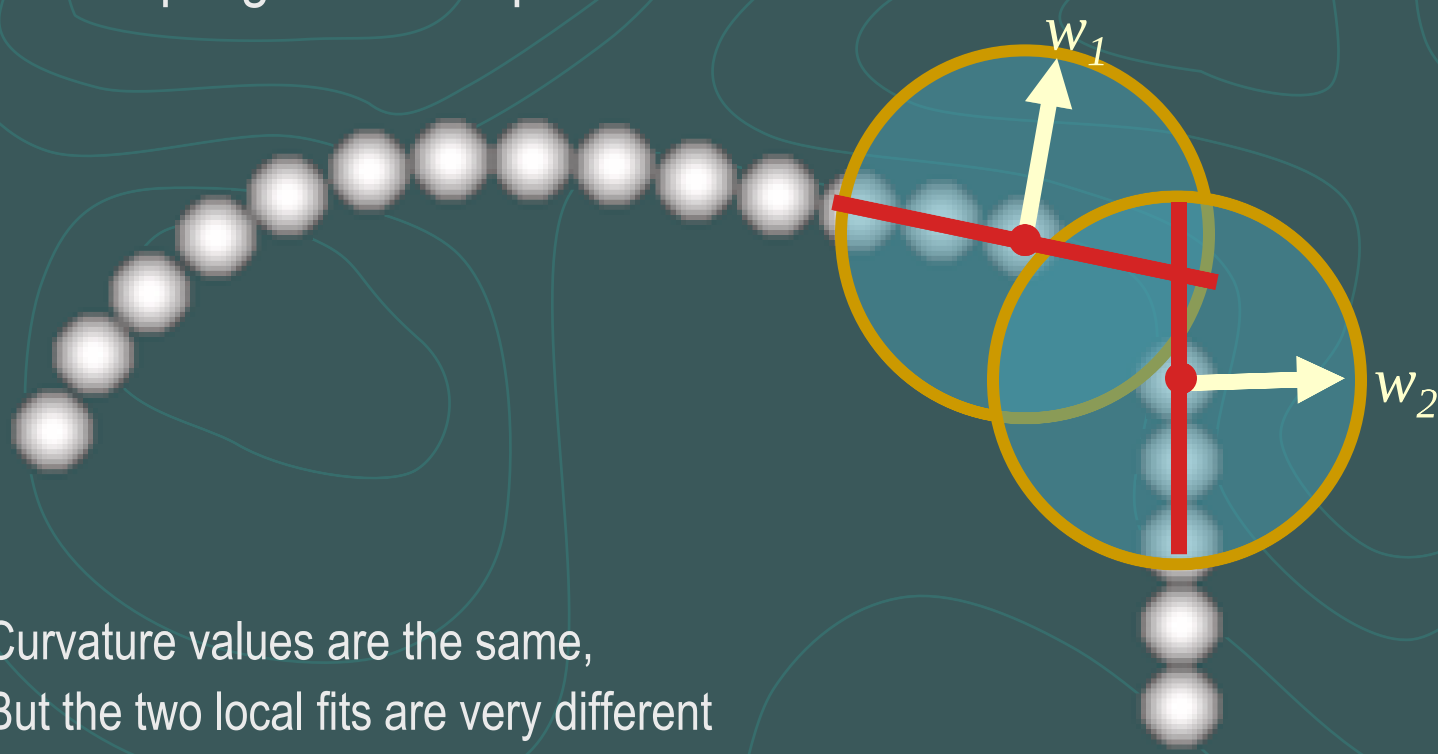
- Curvature computation by estimated biquadratic surface fits (note: assumes additive IID Gaussian noise in the normal direction)
  - Find the local neighborhood
  - PCA➔local coordinate system (u,v,w)
  - Least squares biquadratic fit $w=S(u,v)=a_1u^2+a_2uv+a_3v^2+a_4u+a_5v+a_6$
  - Analytical calculation of mean and Gaussian curvature at $(0,0,S(0,0))$
- Segments: contiguous groups of vertices having the “same” curvature





Regions of Constant Curvature (2)

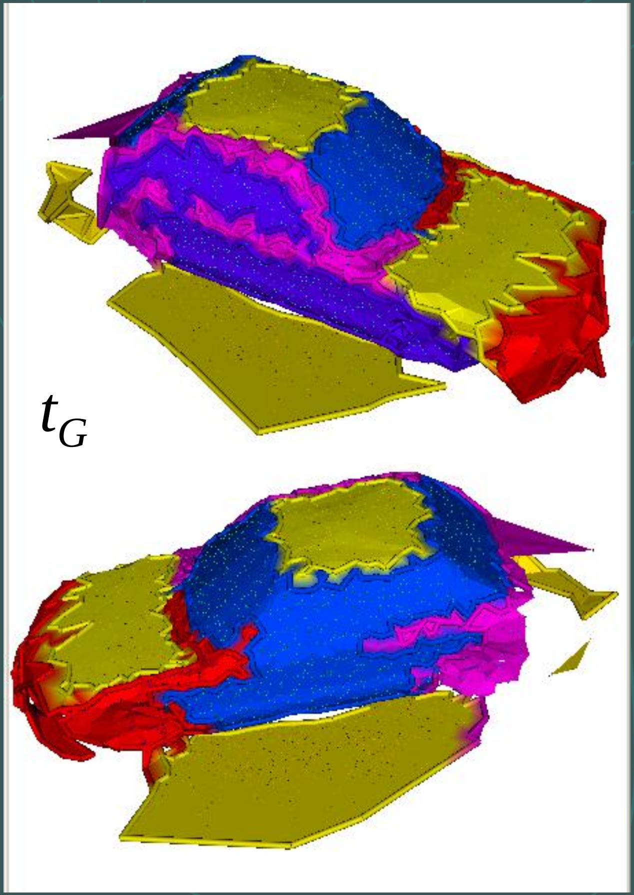
- Under-sampling causes a problem…

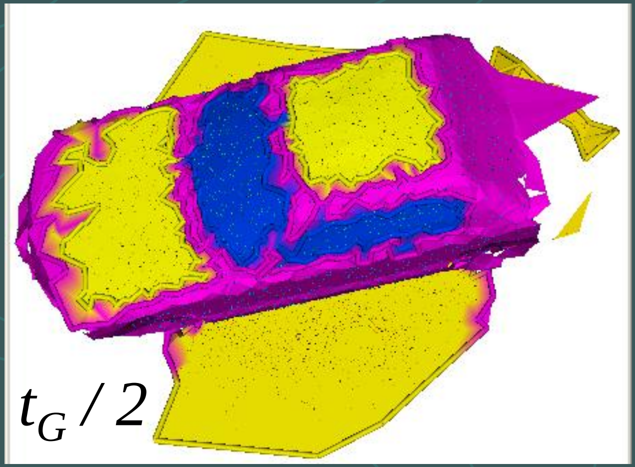


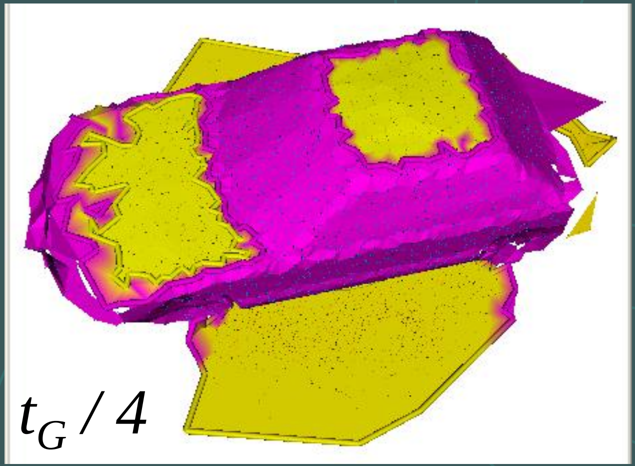
  - Curvature values are the same,
  - But the two local fits are very different

Regions of Constant Curvature:

Sample (Problematic) Segmentations







Note: Magenta denotes segments with highly-inconsistent curvature values ("junk" segments)

Normalized Cuts

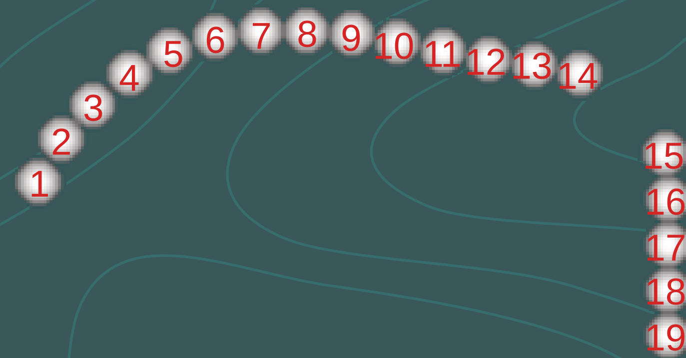
- The idea (density example)

- Inputs, abstractly
  - Graph that connects similar nodes (vertices)
  - An “affinity” measure for each graph arc
- Output
  - A balanced segmentation of the graph

Our Affinity Measure:

What Kind of Affinity Function Do We Want?

Input Data:



Aforementioned-Style

$$
\begin{array}{c|ccccccc}
 & & 12 & 13 & 14 & 15 & 16 & \\
\hline
 & \cdots & & & & & & \cdots \\
12 & & 1 & 0.9 & & & & \\
13 & & 0.9 & 1 & 0.9 & & & \\
14 & & & 0.9 & 1 & 0.9 & & \\
15 & & & & 0.9 & 1 & 0.9 & \\
16 & & & & & 0.9 & 1 & \\
 & \cdots & & & & & & \cdots
\end{array}
$$

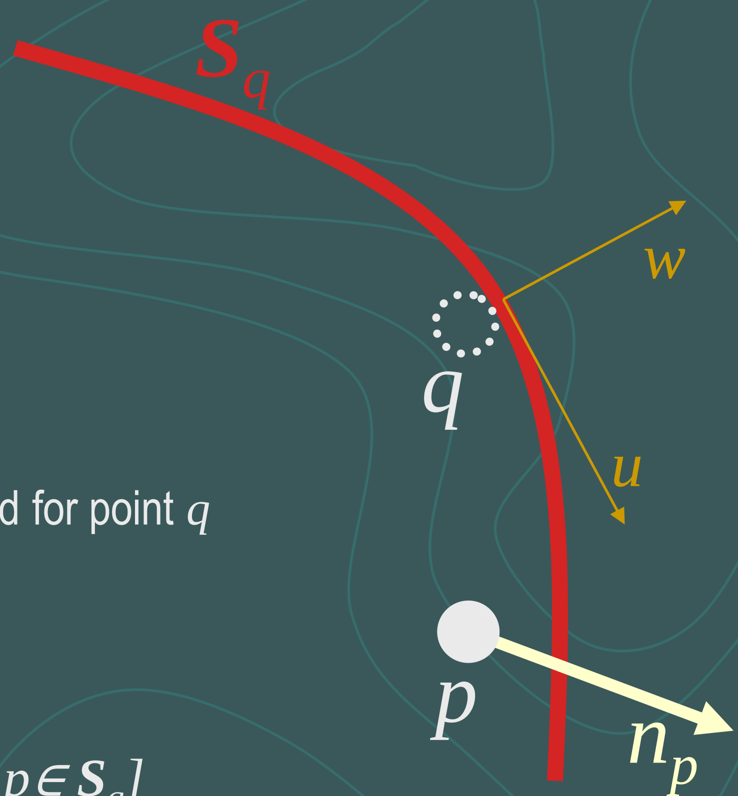
Desired

$$
\begin{array}{c|ccccccc}
 & & 12 & 13 & 14 & 15 & 16 & \\
\hline
 & \cdots & & & & & & \cdots \\
12 & & 1 & 0.9 & 0.8 & 0.1 & 0 & \\
13 & & 0.9 & 1 & 0.9 & 0.1 & 0 & \\
14 & & 0.8 & 0.9 & 1 & 0.2 & 0 & \\
15 & & 0.1 & 0.1 & 0.2 & 1 & 0.9 & \\
16 & & 0 & 0 & 0 & 0.9 & 1 & \\
 & \cdots & & & & & & \cdots
\end{array}
$$

Our Affinity Measure:

Our Affinity Function

- So, we wish to find:
  - $\mathit{affinity}(p,q) \propto$
    $\min(P[(p,n_p)\in \mathbf{S}_q],\ \ P[(q,n_q) \in \mathbf{S}_p])$
    - p := a sampled surface point
    - n_p := surface normal estimated at point p
    - $\mathbf{S}_q$:= a local biquadratic surface estimated for point q *(the "∈" operator means "arose from")*
    - σ_q := RMS error in computing $\mathbf{S}_q$
  - $P[(p,n_p) \in \mathbf{S}_q] = P[p\in \mathbf{S}_q]\ P[n_p\in \mathbf{S}_q \mid p\in \mathbf{S}_q]$



Our Affinity Measure:

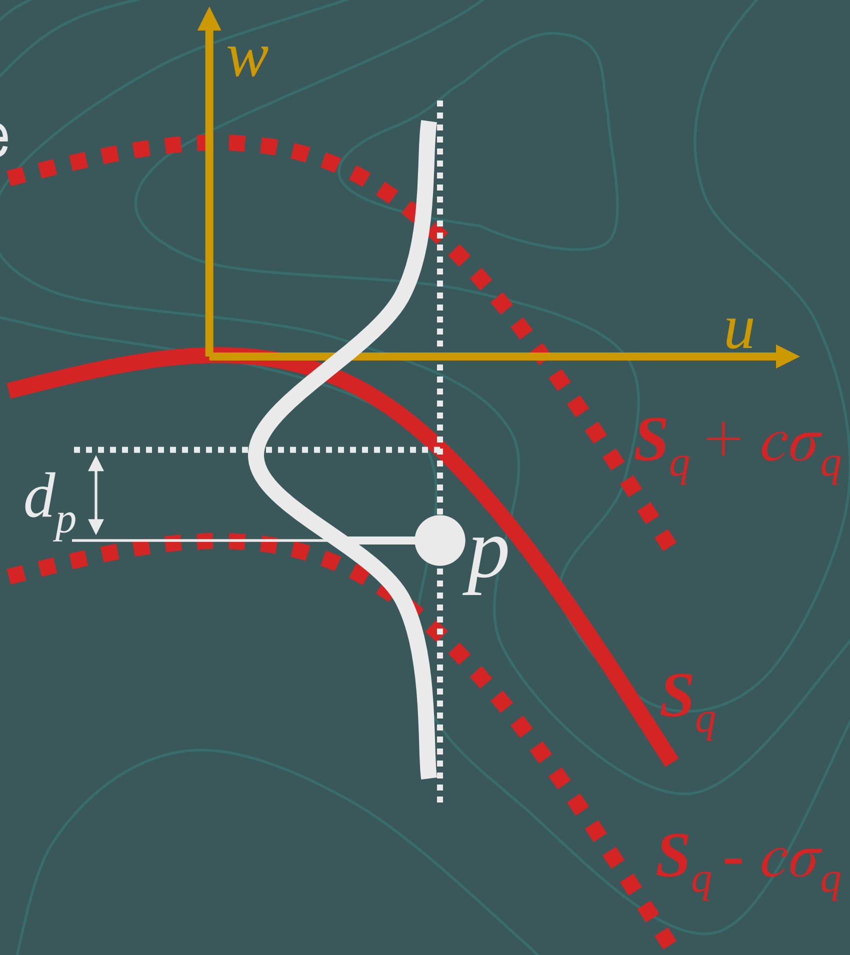
Position Probability

- By a previous assumption, all of the position error is in the w direction, and is distributed as a Gaussian with a variance of σ_q^2.

- $P[p \in S_q \mid \sigma_q] \propto$

$$exp(-d_p^2 / 2\sigma_q^2),$$

where $d_p = | p_w - S_q(p_u , p_v) |$



Our Affinity Measure:

Normal Probability

- The error in the normal measurements can be modeled in 2D as:

  $d_n = |\sin(\angle n_p) - \sin(\angle n_r)|$

  $= |[n_p]_u - [n_r]_u|$

  where

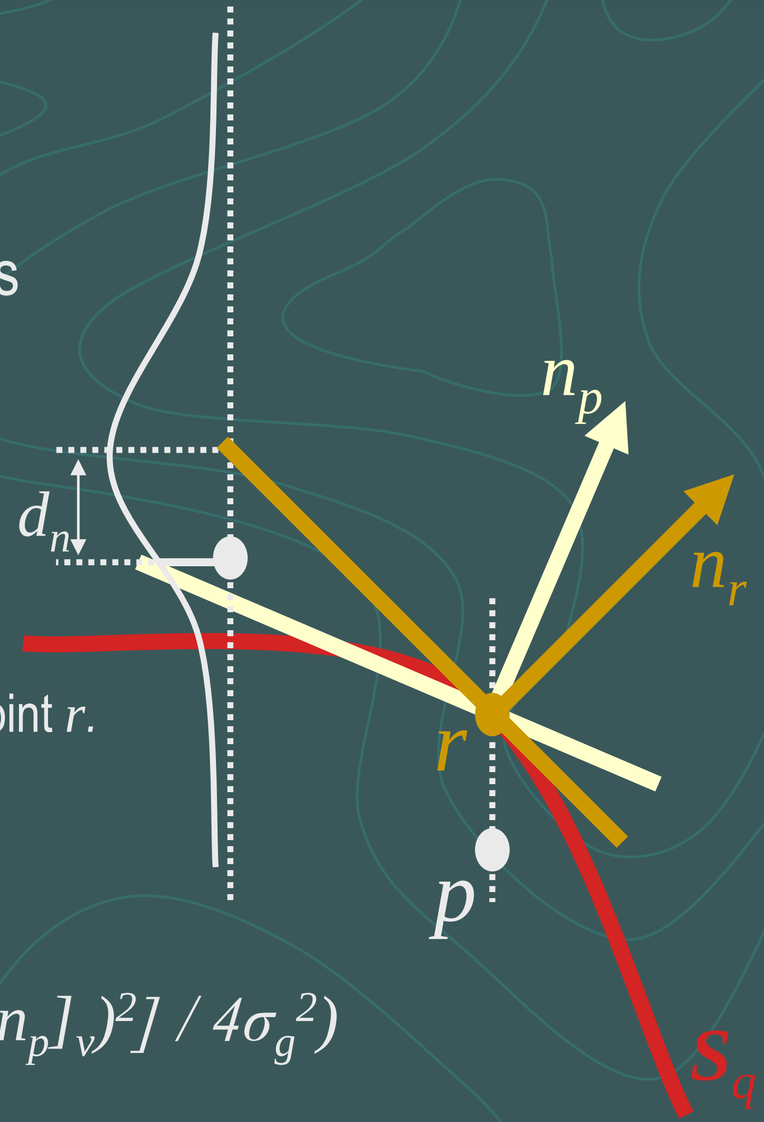
  $r := [p_u \quad p_v \quad S_q(p_u, p_v)]^T$

  $n_r :=$ The normal calculated from S_q at point r.

- Extending to 3D,

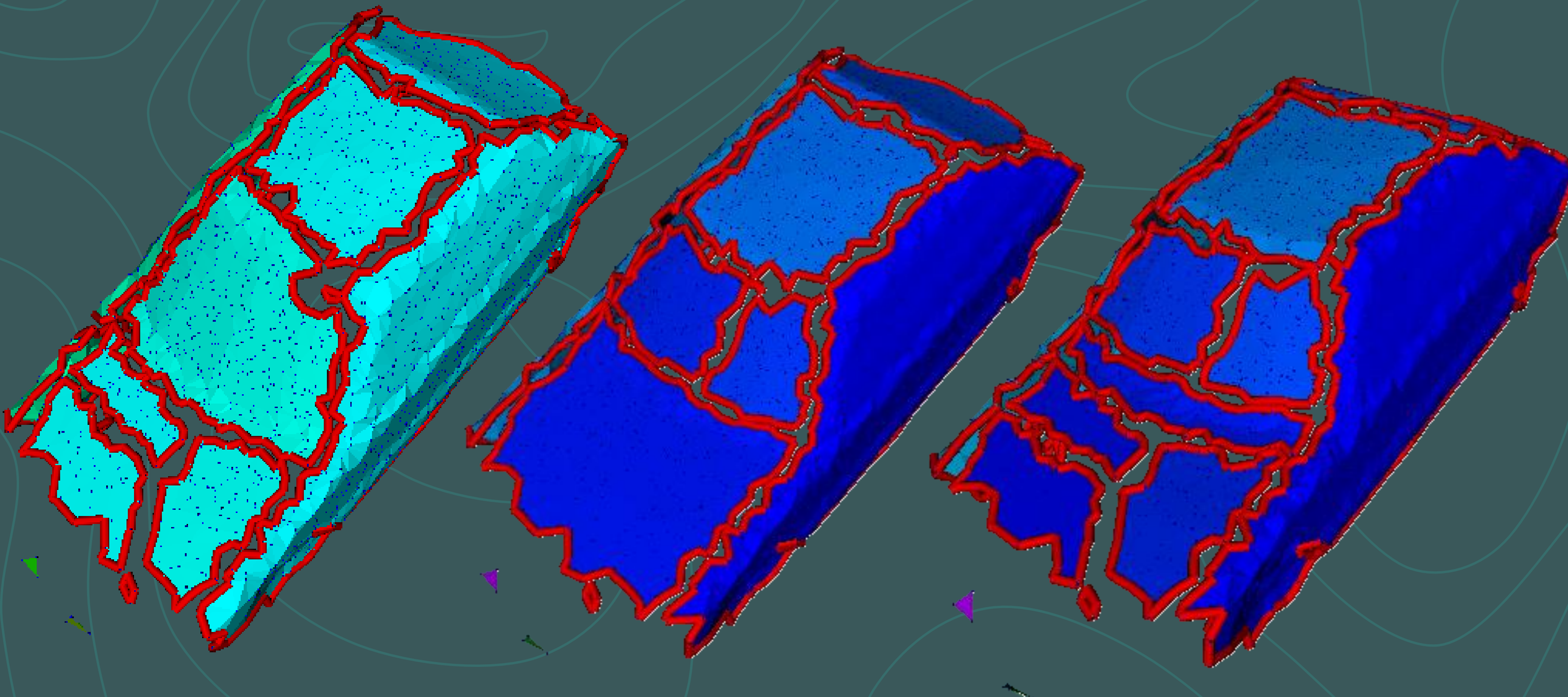
  $P[n_p \in \mathbf{S}_q \mid p \in \mathbf{S}_q] \propto$

  $\exp([-([n_r]_u - [n_p]_u)^2 - ([n_r]_v - [n_p]_v)^2] / 4\sigma_g^2)$



Our Affinity Measure:

Initial Results



Smaller affinity neighborhood

Baseline

Let nCuts keep going

Future Work

- Other affinity measures
  - A more rigorous derivation of $P[n_p \in \mathbf{S}_q \mid p \in \mathbf{S}_q]$
- Testing on more data
  - 5 objects
  - Circling vs. double fly-by
  - Varying degrees of clutter
- Object recognition
  - The proof must be in the pudding…

References

- J. Shi and J. Malik. “Normalized cuts and image segmentation”. *IEEE PAMI*. Vol. 22 No. 8. Aug. 2000. Pgs. 888-905.
- R. Srikantiah. *Multi-Scale Surface Segmentation and Description for Free Form Object Recognition*. M.S. Thesis. The Ohio State University. 2000.
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