

# Processing 3D Laser Scanner Data for Automotive Styling Design

Ph.D. Thesis Proposal

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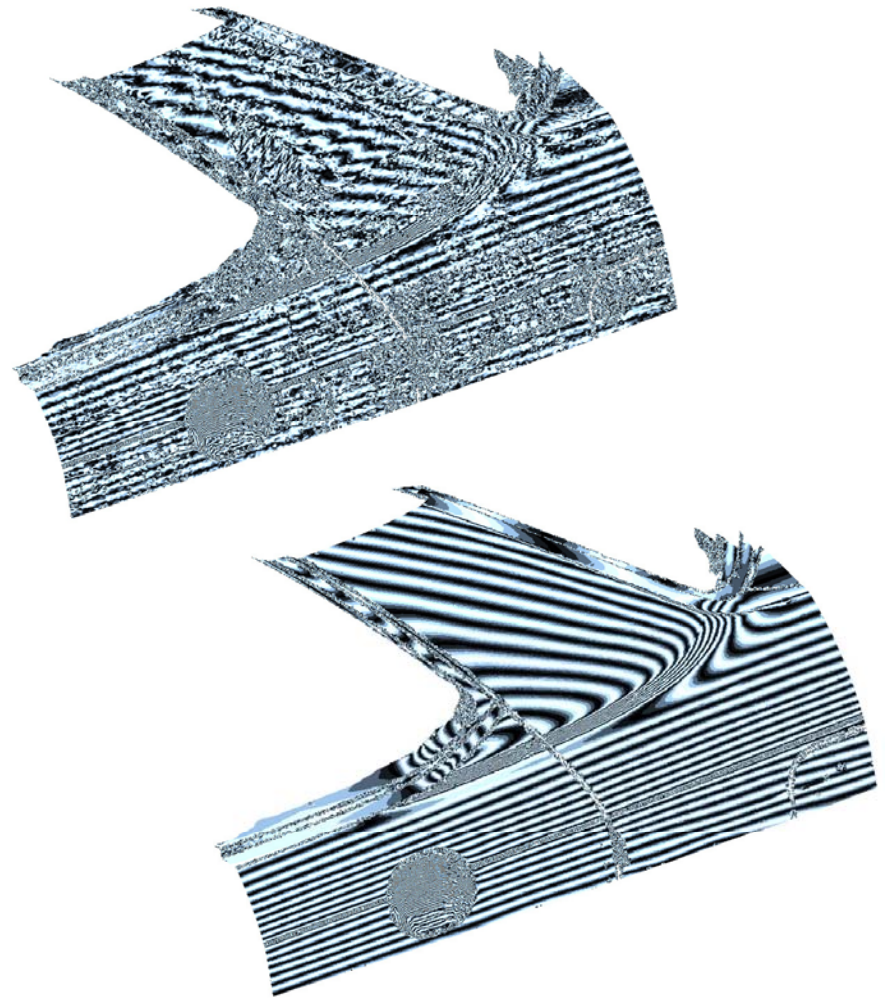
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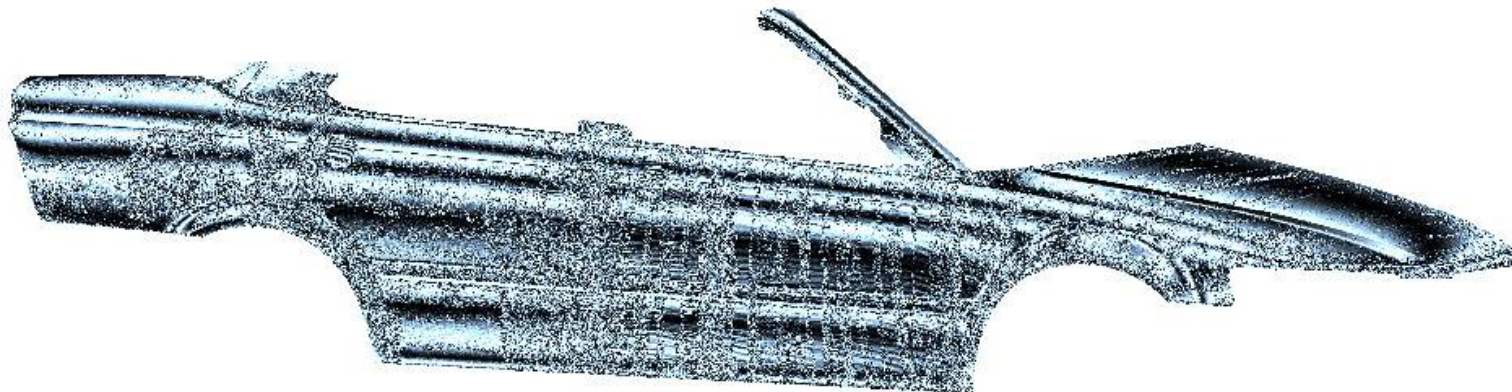


# Laser Scanner Technology

- Can quickly measure 3D surface coordinates without contact
- Accurate and easy to use
- Used in automotive styling design to digitize models
- Scanned data can be used for:
  - Testing engineering requirements
  - Aesthetic interrogation
  - Surfacing the final part



<http://www.steinbichler.de>



# Problem Statement

- Laser-scanner data often needs significant preprocessing before it is useful
- Automotive styling design issues are not addressed by existing algorithms
  - How to remove geometric noise from the data without deforming it or smoothing sharp edges?
  - How to group the points into regions closely approximated by single surfaces?
  - Can we create a piecewise-smooth reconstruction of the part that satisfies both aesthetic and engineering constraints?

# Automotive Design Requirements

- Design Constraints
  - Scanner accuracy
  - Tolerances required for design and manufacture
  - These bound the deformation of the data and the accuracy of surface fitting and surface reconstruction
- Aesthetic Constraints
  - A  $k$  differentiable surface has  $k-1$  differentiable reflection lines: smooth reflection lines require a twice differentiable surface
  - Character lines are sharp edges that create a distinctive shape – these sharp edges must be preserved
  - Principle of simplest shape: the resulting surface must be free of unnecessary undulations

# Thesis Contributions

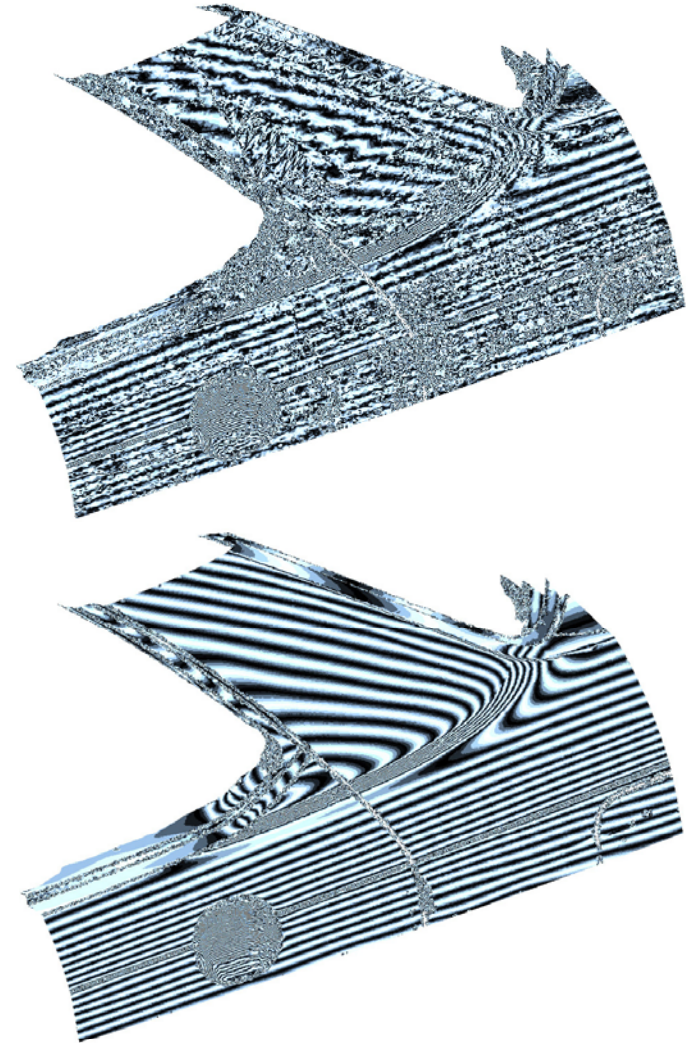
- Mesh Smoothing
  - Creates an aesthetically pleasing surface
  - Minimizes mesh deformation
  - Preserves sharp edges
- Surface Extraction
  - Estimates curvatures and noise levels on the data
  - Detects sharp edges
  - Segments data into regions approximated by single surfaces
  - Fits surfaces to a specified tolerance
- Surface Reconstruction (proposed)
  - Will reconstruct objects with large smooth surfaces, smooth blends between surfaces, and sharp edges
  - Will bound the accuracy and geometric continuity of the reconstructed object

# Algorithms

- Mesh Smoothing
- Surface Extraction from Meshes
- Surface Extraction from Point-Sampled Data
- Surface Reconstruction Proposal
- Summary

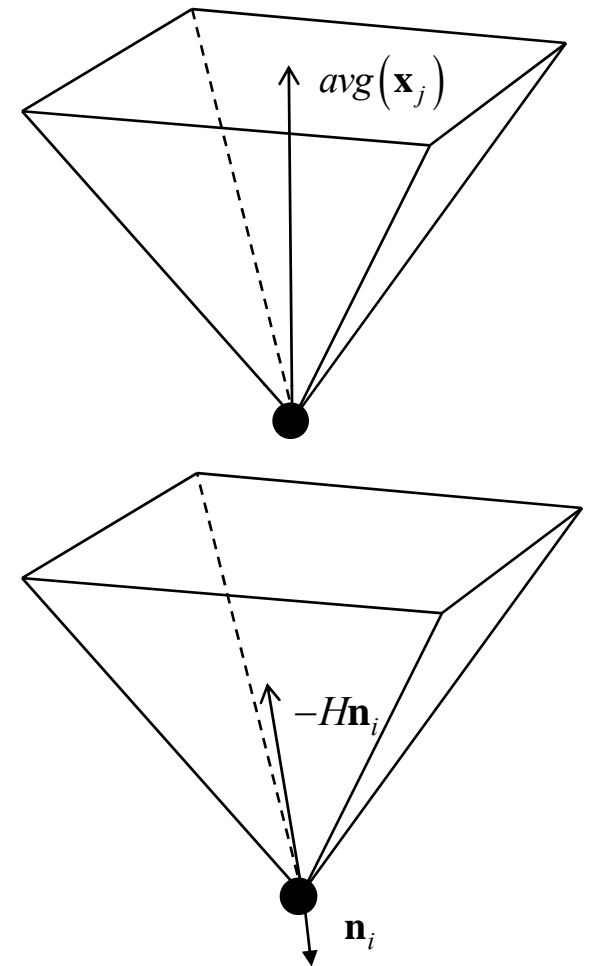
# Problem Statement

- Goal: remove geometric noise from a mesh with edge preservation and minimal deformation
- Deformation must be within laser-scanner and design tolerances
- Result must be smooth over large scales with sharp edges preserved
- The smoothed mesh will be used for aesthetic interrogation and patch fitting for design



# Existing Smoothing Methods

- Diffusion: move each vertex to a weighted average of the positions of its neighbors [1]
- Curvature Flow: move each vertex in its normal direction a distance equal to the mean curvature [2]
  - Both these methods can cause distortion, so using them requires a compromise
- Normal Maps: smooth the normals first, then find vertex positions that satisfy the normal field [3]



[1] Kobbelt, et al., *Geometric Modeling Based on Polygonal Meshes (tutorial)*, EUROGRAPHICS 2000.

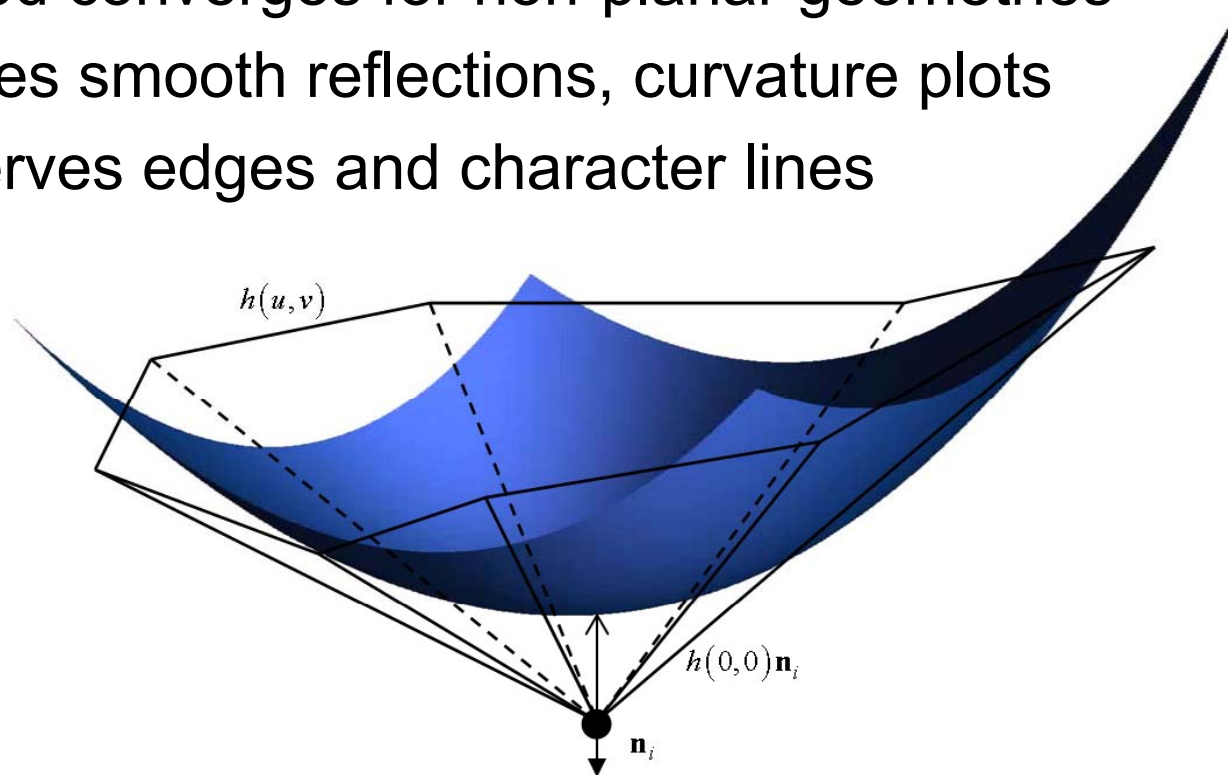
[2] Desbrun, et al., *Implicit Fairing of Irregular Meshes Using Diffusion and Curvature Flow*, SIGGRAPH 99.

[3] Tasdizen, et al., *Geometric Surface Smoothing via Anisotropic Diffusion of Normals*, IEEE Visualization 2002.



# Polynomial Fitting Solution

- Each vertex is moved onto a polynomial surface approximating its neighborhood
- User can control polynomial order, neighborhood size, and threshold angle
- Method converges for non-planar geometries
- Creates smooth reflections, curvature plots
- Preserves edges and character lines



# Differential Geometry

- The neighborhood of every point on a smooth surface is defined by a 2D Taylor series in a local coordinate system:

$$h(u, v) = \sum_{k=2}^n \frac{1}{k!} \left( u \frac{\partial}{\partial u} + v \frac{\partial}{\partial v} \right)^k h(0, 0)$$

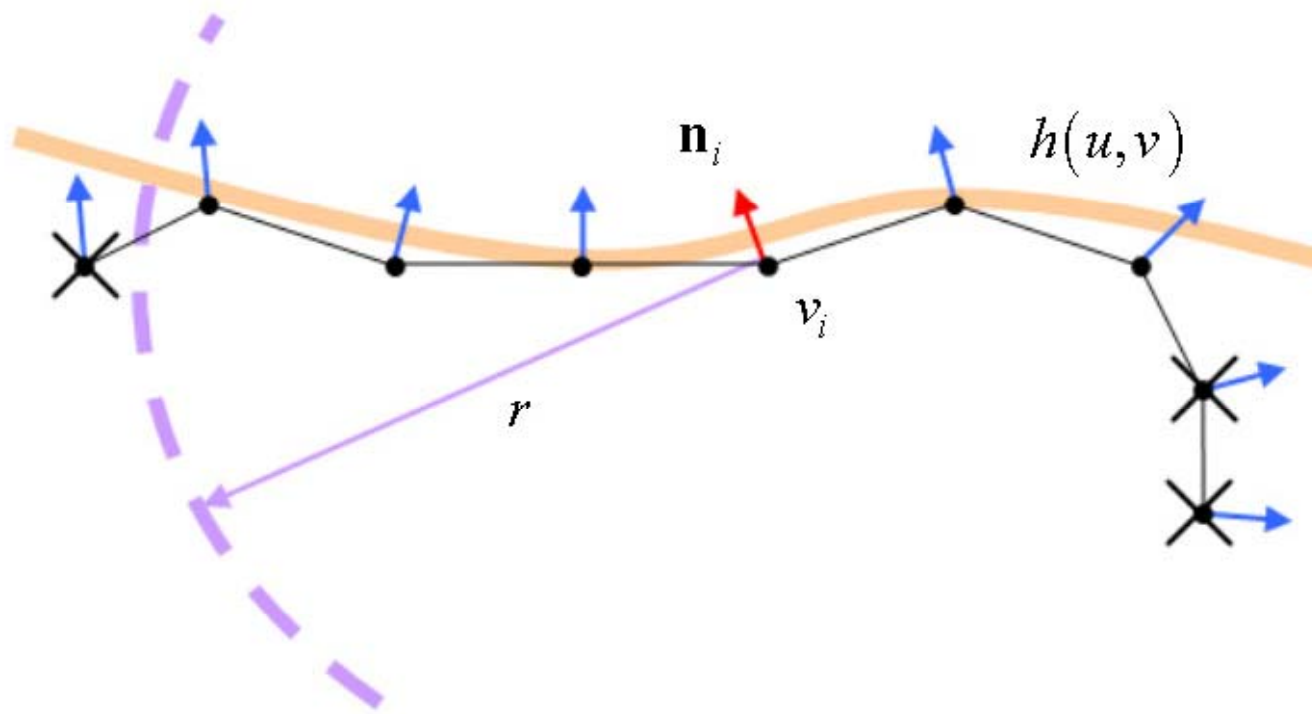
- The Taylor series determines the differentiability of the surface at the point
- We find the coefficients of truncated approximation of the Taylor series

$$h(u, v) = a_{00} + a_{10}u + a_{01}v + a_{20}u^2 + a_{11}uv + a_{02}v^2$$

- Approximating polynomial is found with a linear least-squares problem solved by Cholesky decomposition

# Vertex Neighborhoods

- Create a neighborhood by adding vertices with positions and normals close to that of the target vertex
- This creates pseudo-planar neighborhoods that don't include sharp edges



# Implementation

- For each vertex
  - Grow a neighborhood using breadth-first search with distance and normal-deviation constraints
  - Find neighborhood vertex positions in local coordinate system
  - Least squares fit a polynomial to the vertices in the local coordinate system
  - Move the target vertex onto the polynomial
- User selects neighborhood width, polynomial order, and threshold angle

Automobile C-Pillar

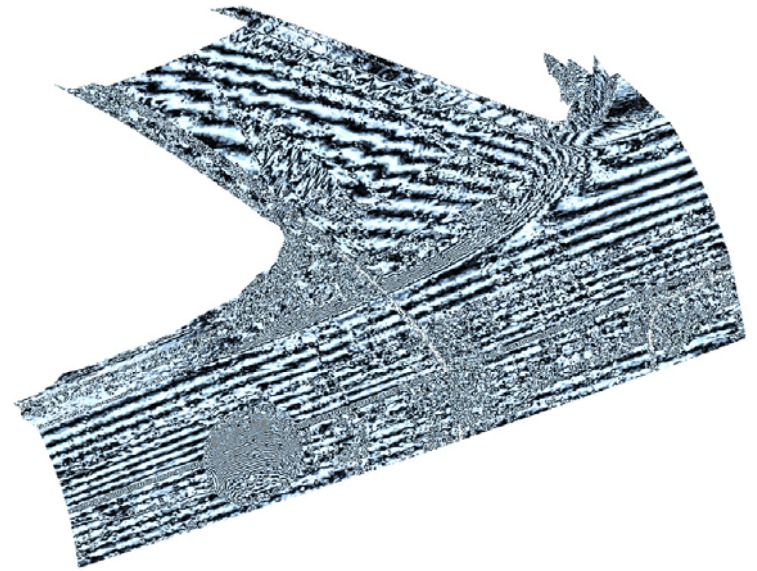
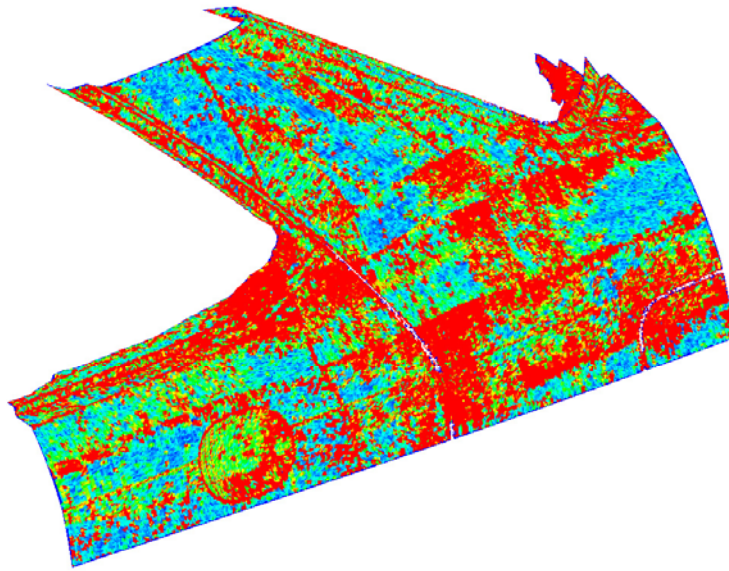
99,790 vertices

# Results

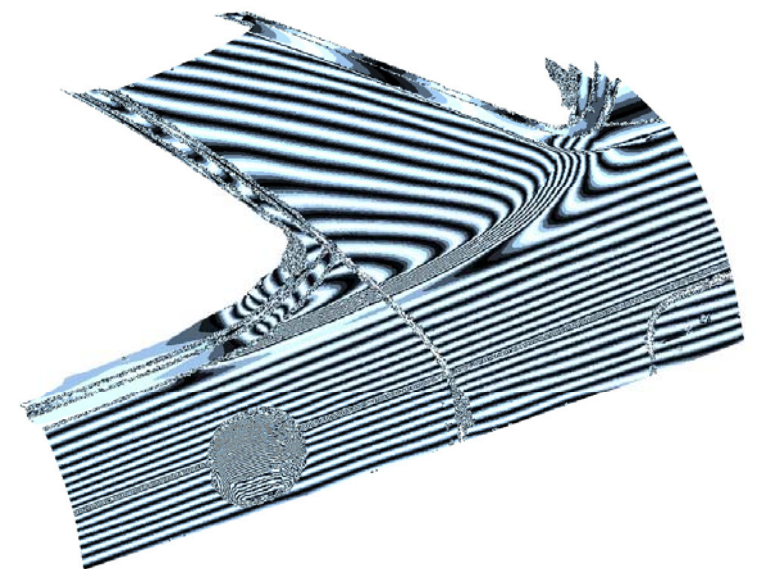
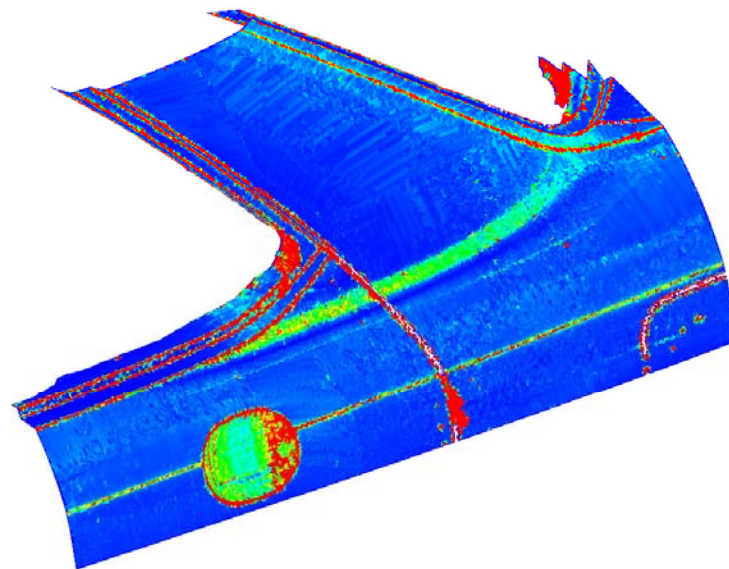
Curvature

Reflections

Original



Smoothed



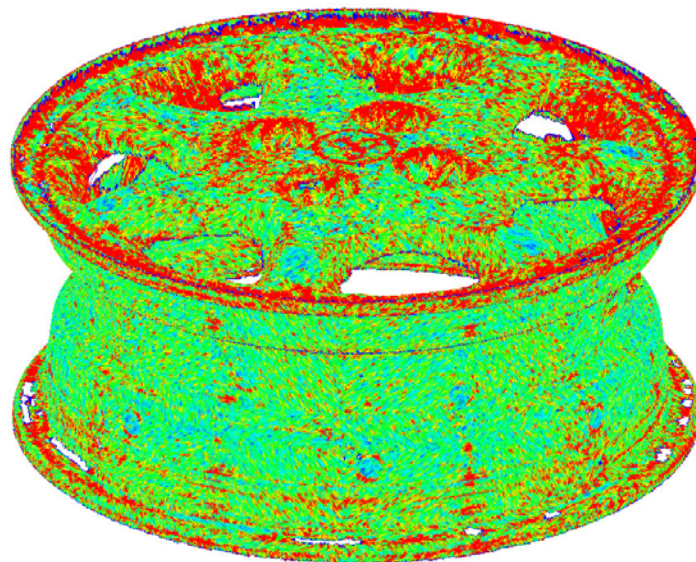
Wheel Rim  
366,920 vertices

# Results

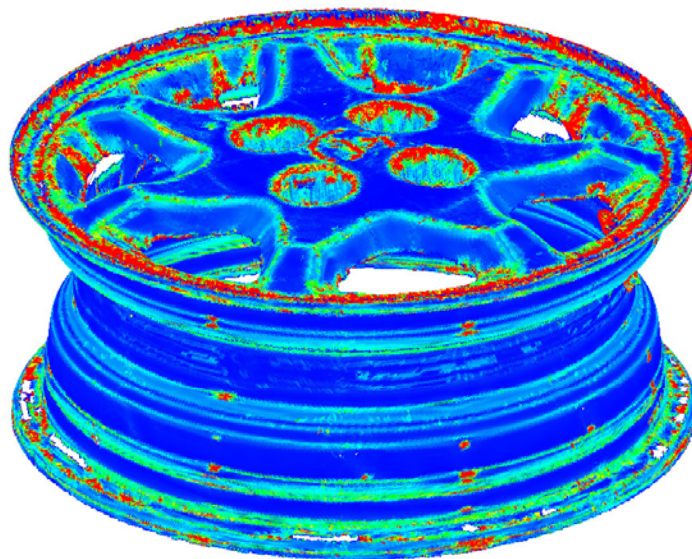
Curvature

Reflections

Original



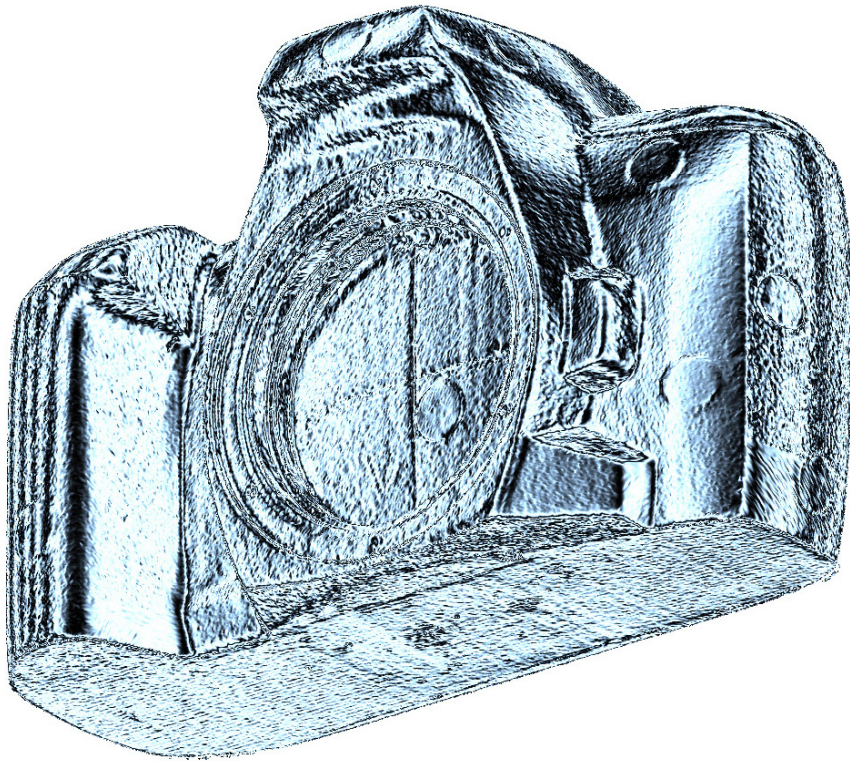
Smoothed



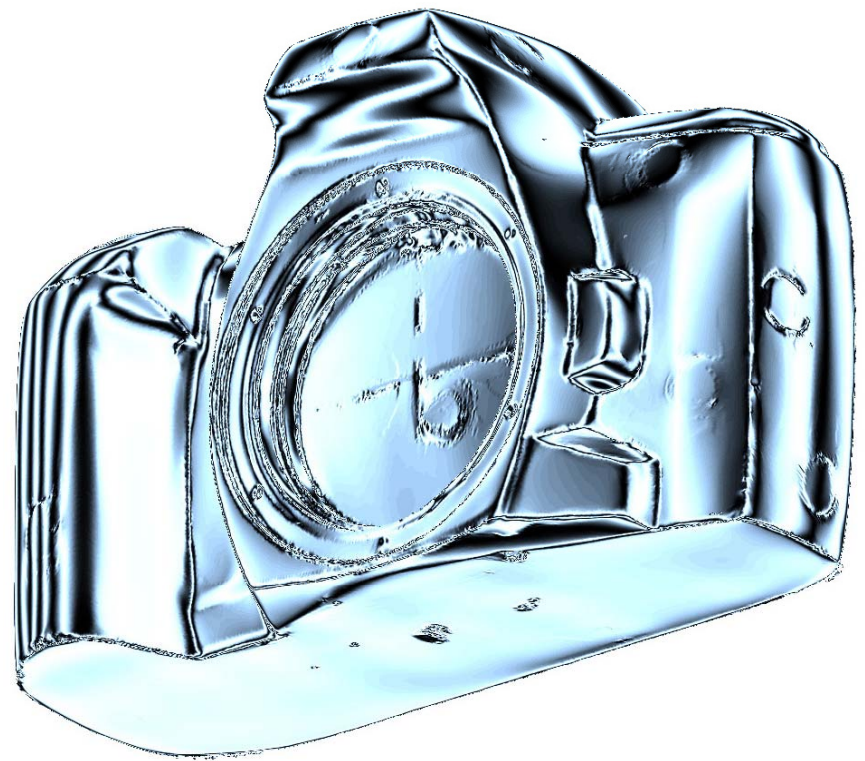
SLR Body

606,254 vertices

# Results



Original



Smoothed

# Algorithms

- Mesh Smoothing
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- Surface Extraction from Point-Sampled Data
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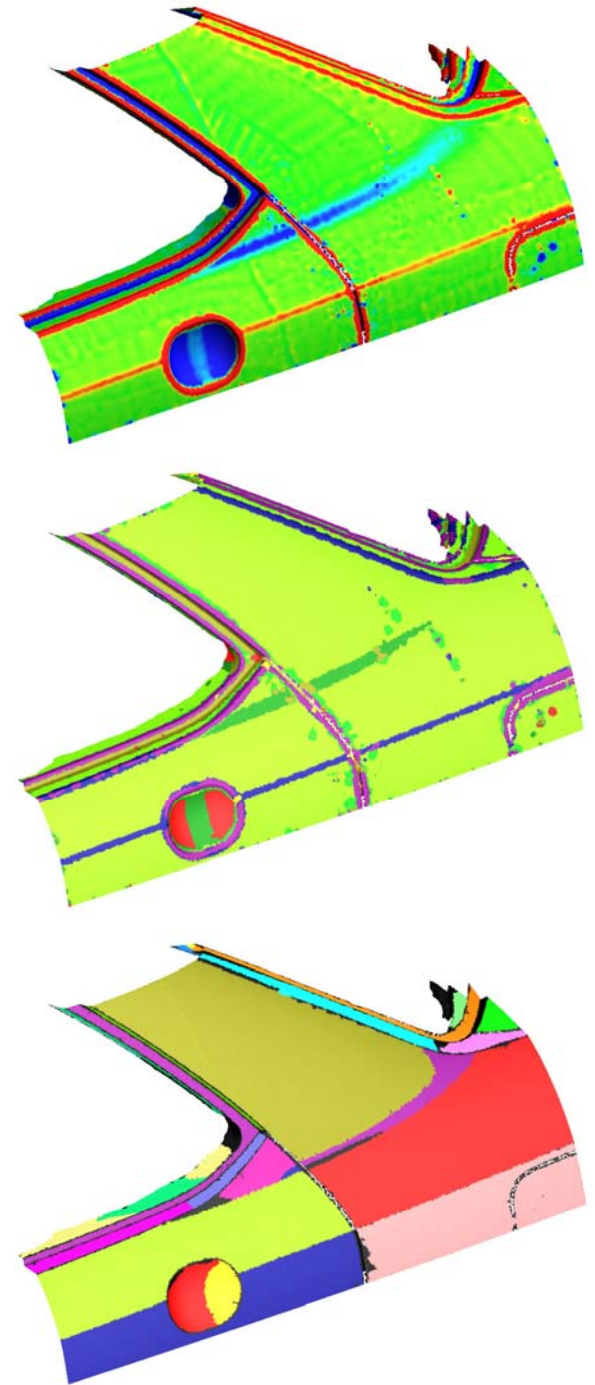


# Problem Statement

- Must create a concise surface-based representation of the object from the scanned data
- This is a manually intensive and time-consuming procedure
- How can we automatically segment a dense, noisy mesh into groups of vertices approximated by single surfaces and then output the surfaces themselves?
  - Segments should be as large as possible
  - Surface approximations must be accurate
- A designer can easily modify the extracted surfaces to create a final design

# Algorithm Summary

- Approximate vertex neighborhoods with polynomials
  - Estimate surface curvatures
  - Estimate noise levels
  - Detect sharp edges
- Filter curvatures and label vertices by curvature-signs
- Contract labeled regions to create seed regions
- Grow seed regions by iterating between region growing and surface fitting
- Regions are grown by testing vertices for geometric compatibility with the approximating surfaces



# Related Work

- Besl and Jain introduced region growing for images and range data [1]
  - We generalize this approach to dense, noisy, unstructured data
- Direct segmentation: hierarchical subdivision by testing neighborhoods for compatibility with increasingly complex analytic surfaces [2]
  - Not clear how to use with freeform surfaces
- Recover-and-select: simultaneously grow randomly placed regions while culling non-optimal models [3,4]
  - We place seed regions carefully for computation efficiency

[1] Besl and Jain. *Segmentation Through Variable-Order Surface Fitting*. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1988.

[2] Benkő and Várady. *Segmentation Methods for Smooth Point Regions of Conventional Engineering Objects*. *Computer-Aided Design Journal*, 2004.

[3] Leonardis, et al. *Superquadrics for Segmenting and Modeling Range Data*. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1997.

# Noise and Curvature Estimation

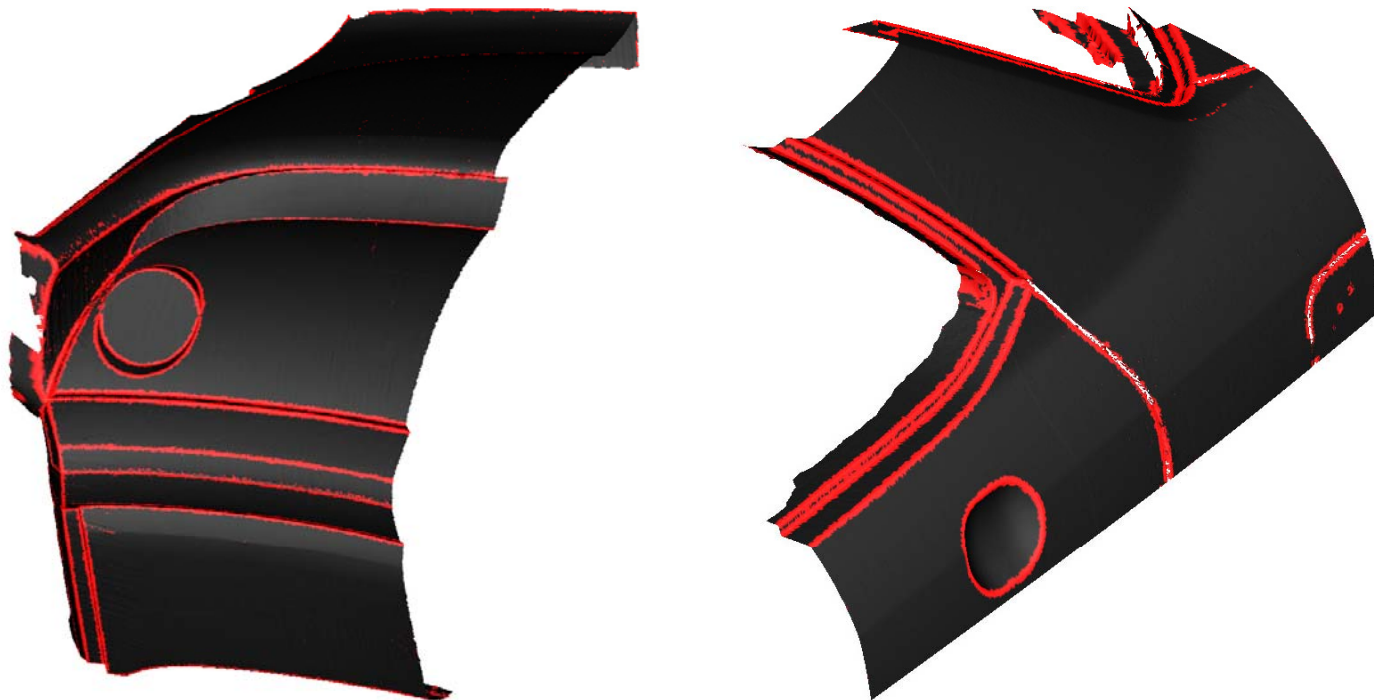
- We approximate the points within a ball centered at each vertex with a quadric polynomial

$$h(u, v) = a_{00} + a_{10}u + a_{01}v + a_{20}u^2 + a_{11}uv + a_{02}v^2$$

- From this polynomial we calculate the Gaussian, mean, and principal curvatures
- The  $G^0$  noise is calculated by  $\varepsilon_i^0 = |a_{00}|$
- The  $G^1$  noise is calculated by  $\varepsilon_i^1 = \cos^{-1}(\mathbf{n} \cdot \mathbf{n}_i)$
- For the  $G^0$  and  $G^1$  noise, we find the value that is larger than that of a certain percentage of the other vertices
- These values will be the compatibility thresholds for region growing

# Sharp Edge Detection

- If the smallest radius of curvature at a vertex is small compared to the mesh density, a sharp edge is indicated
- We do not grow regions from sharp edges
- Mathematically, a sharp edge is likely if  $\frac{1}{|\mathcal{K}_{\max, i}|} < 10 l_{\text{avg}, i}$



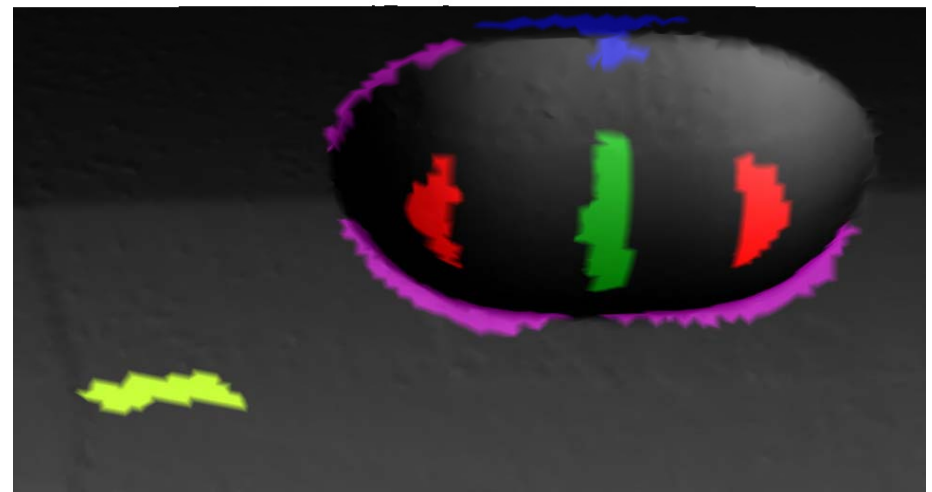
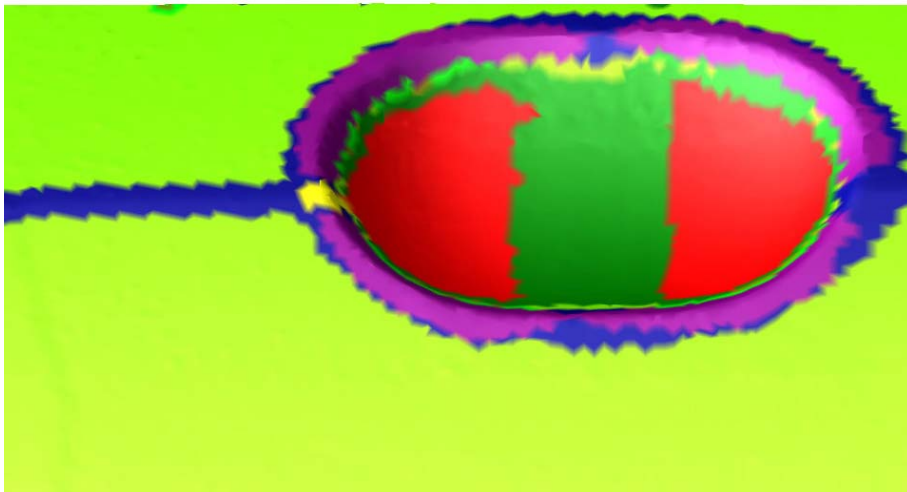
# Surface-Type Labeling

- We apply median and mean filters to the curvatures to despeckle and smooth them
- Then we use the signs of the filtered Gaussian and mean curvature to label the vertices

	$K > 0$	$K = 0$	$K < 0$
$H < 0$	Peak	Ridge	Saddle Ridge
$H = 0$	(none)	Flat	Minimal Surface
$H > 0$	Pit	Valley	Saddle Valley

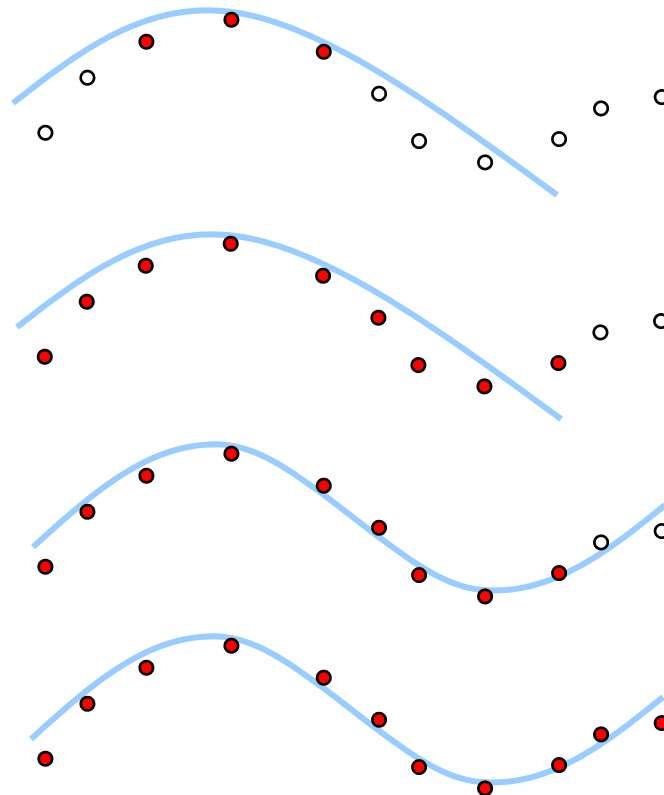
# Seed Regions

- Region growing is most effective when vertices on the boundary of the growing region are geometrically compatible with those already in the region
- Cluster points with the same surface-type labels
- Contract these clusters to form seed regions



# Region Growing

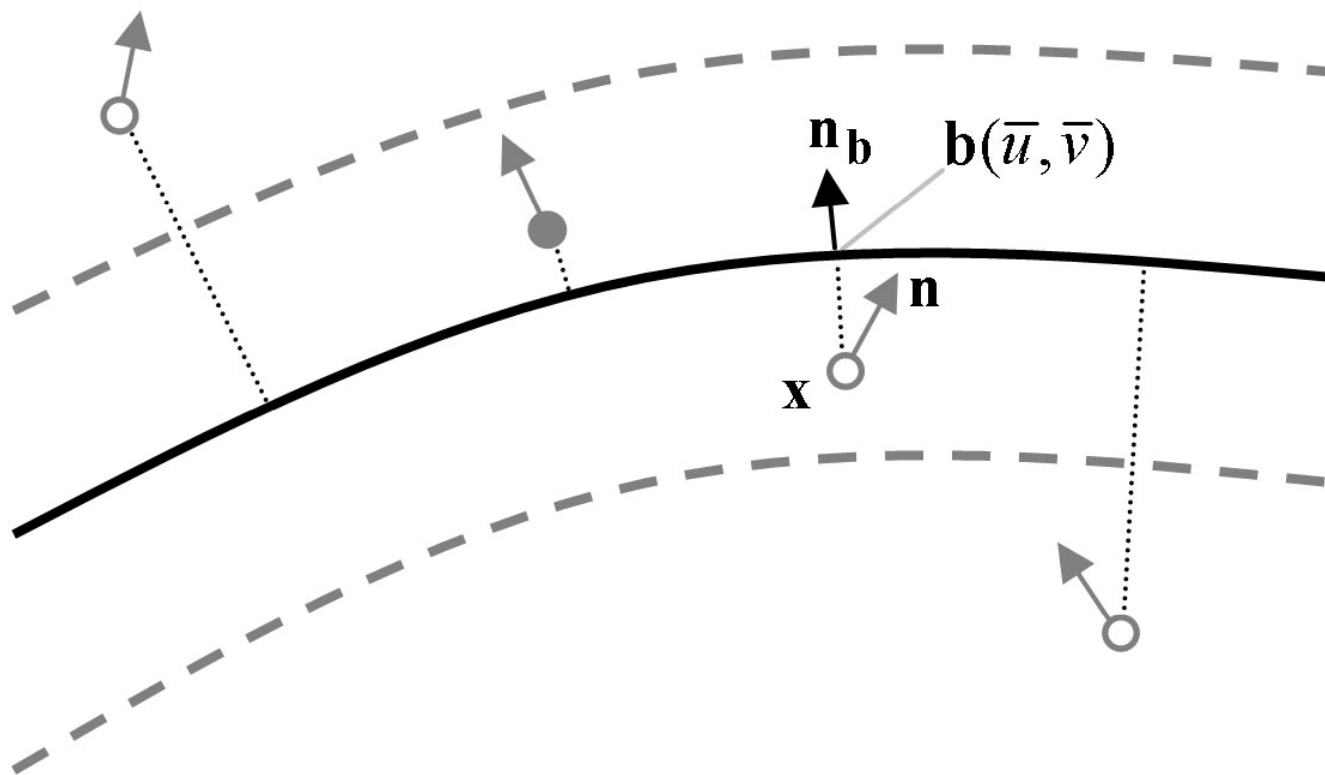
- Seed regions lie within large groups of vertices with identical geometric properties
- A surface approximating the seed region likely approximates the nearby vertices well





# Geometric Compatibility

- We fit a surface to the seed region
- Given a point  $\mathbf{x}$  and a parametric surface  $\mathbf{b}(u,v)$ 
  - $\mathbf{x}$  is  $G^0$ -compatible if  $\|\mathbf{x} - \mathbf{b}(\bar{u}, \bar{v})\| < \varepsilon^0$
  - $\mathbf{x}$  is  $G^1$ -compatible if  $\cos^{-1}(\mathbf{n}, \mathbf{n}_b) < \varepsilon^1$



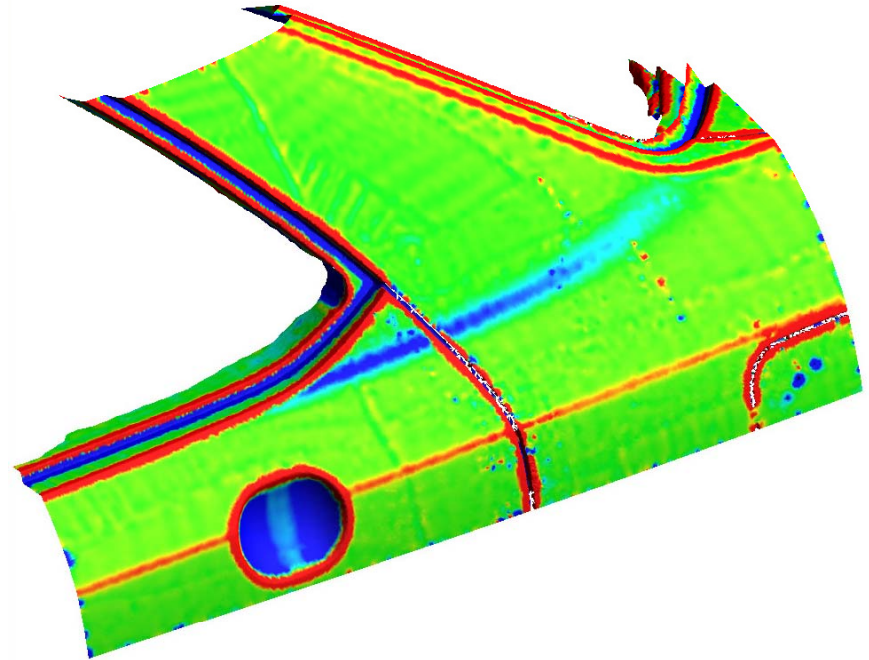
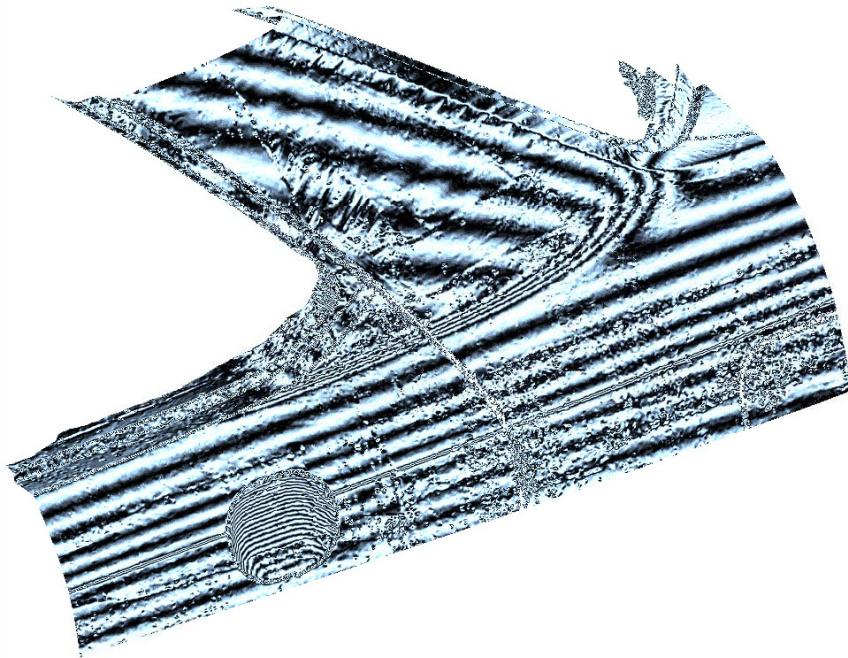
# Surface Fitting

- The region-growing algorithm can be used with any class of surfaces that allows
  - approximation (surface fitting)
  - differentiation
  - point projection (testing geometric compatibility)
- We use bicubic Bézier surfaces

$$\mathbf{b}(u, v) = \sum_{i=0}^3 \sum_{j=0}^3 \mathbf{p}_{i,j} B_i^3(u) B_j^3(v), \quad 0 \leq u, v \leq 1$$

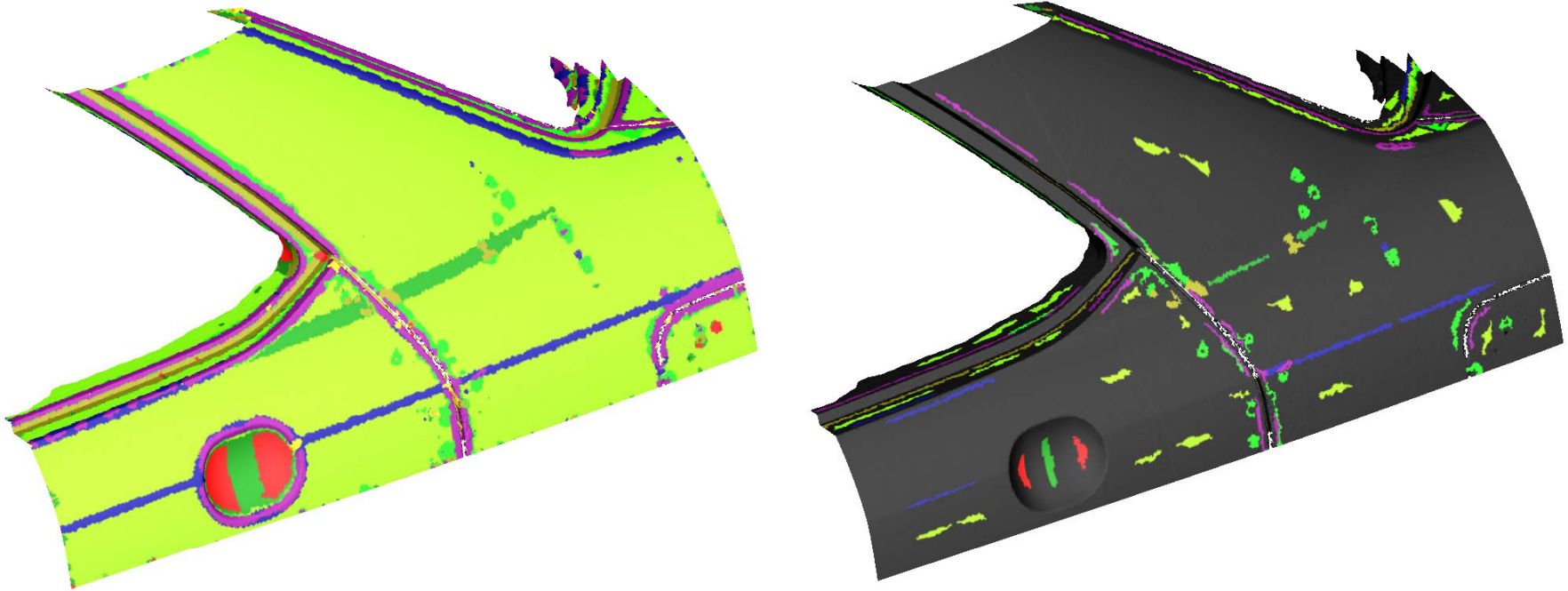
- First we get an initial parameterization for the region
- Then we iterate between surface fitting and parameterization to get a good fit

# Results



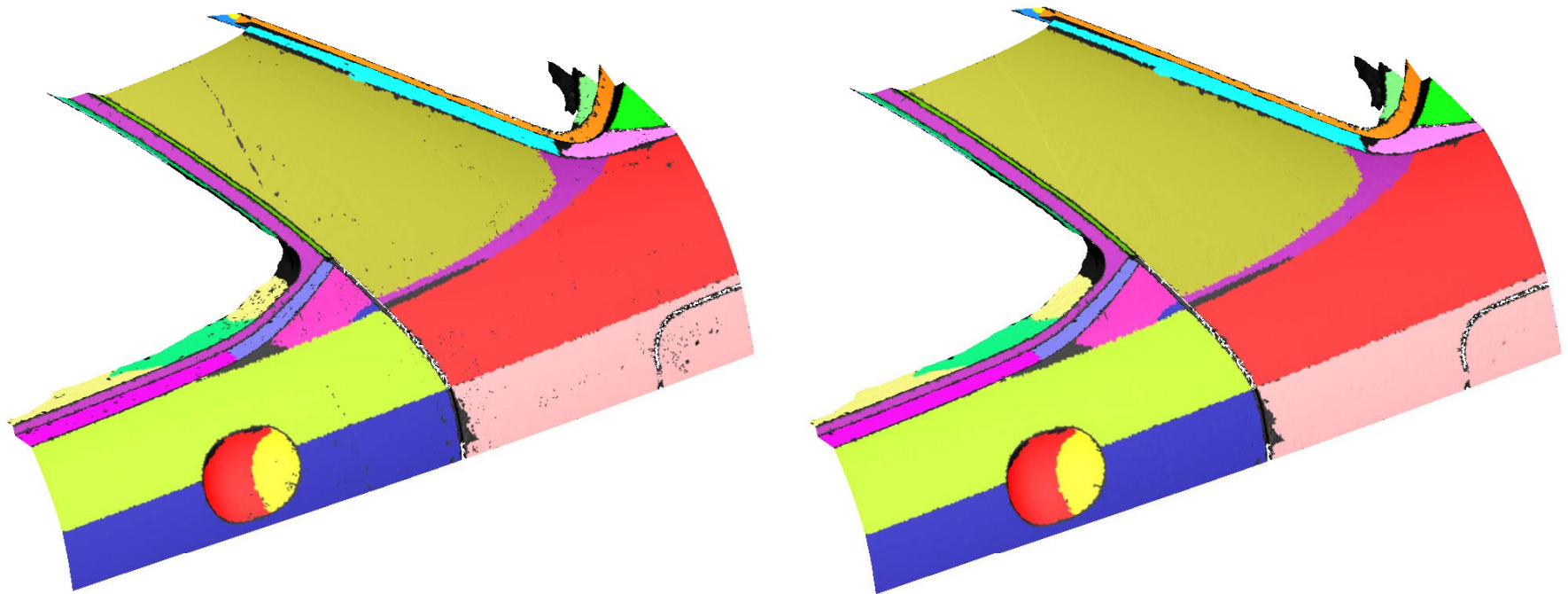
- Simulated reflection lines on the raw mesh show how noisy the geometry is
- The estimated curvatures are shown on the right

# Results



- We label vertices using the signs of the Gaussian and mean curvatures
- Then we contract the labeled regions to form seed regions

# Results



- Each color corresponds to a region of vertices approximated by a single surface
- As a last step, we remove holes in the segmentation caused by outlier noise

# Results

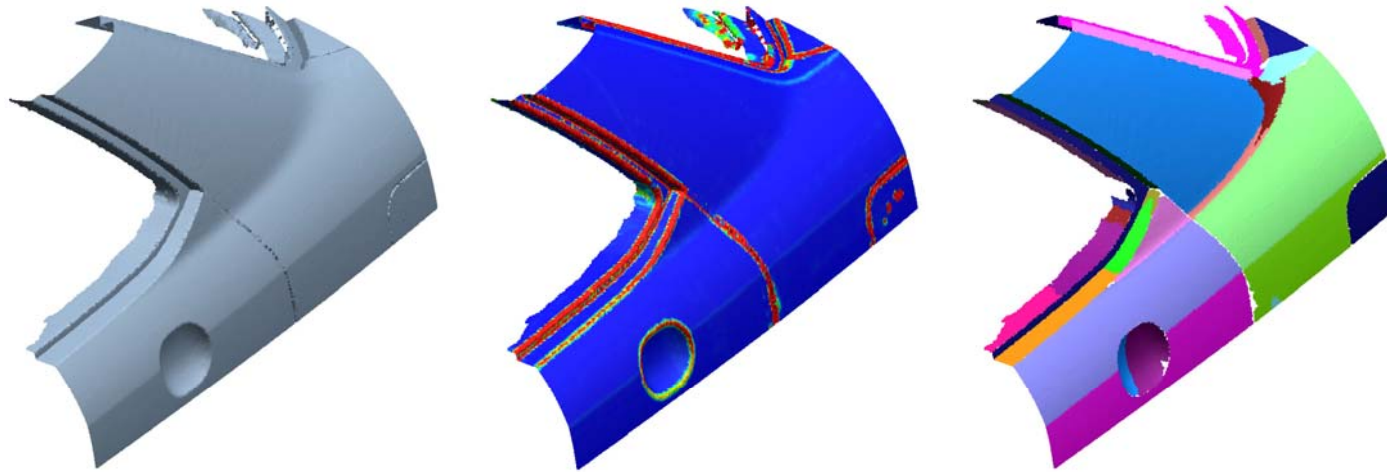


- Here we projected the segmented vertices onto the extracted surfaces
- Note the smooth reflection lines on the extracted surfaces

# Algorithms

- Mesh Smoothing
- Surface Extraction from Meshes
- **Surface Extraction from Point-Sampled Data**
- Surface Reconstruction Proposal
- Summary

# Motivation



- Using a mesh for surface extraction requires too much computer memory
- Can we modify the algorithm and reduce the data representation so we can process very large models?
- When the data is very dense, we can replace topology with spatial proximity!



# Algorithm

- Grow regions from seed points in in order of increasing surface variation
- Region Growing
  - Use points near the seed point to fit an initial surface approximation for region growing
  - Grow the region by adding points that are geometrically compatible with the underlying surface
  - Once all compatible points have been added, fit a new surface to the region to improve the approximation
  - Use the new surface to re-grow the region
- Repeat until region size stops increasing

# Surface Variation

- Estimates local surface properties on point clouds
- Like finding the mean and variance of a 1D distribution
- Let  $\mathbf{N}(\mathbf{x}_i)$  be the  $k$ -nearest neighbors of a point  $\mathbf{x}_i$
- Then the covariance matrix of the points is

$$\mathbf{C} = \sum_{\mathbf{y} \in \mathbf{N}(\mathbf{x}_i)} (\mathbf{y} - \bar{\mathbf{x}}) \cdot (\mathbf{y} - \bar{\mathbf{x}})^T$$

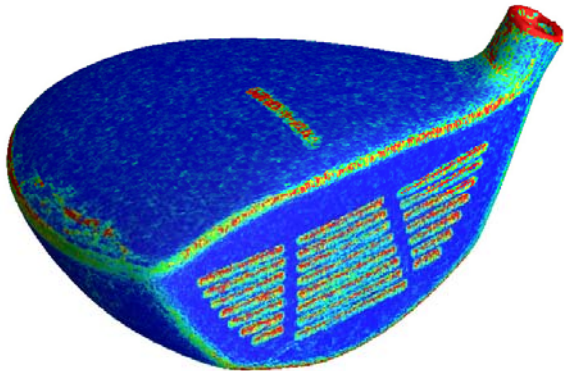
- The eigenvalues of this matrix measure the variance of  $\mathbf{N}(\mathbf{x}_i)$  in the directions of the eigenvectors
- The surface variation is

$$\sigma_k(\mathbf{x}_i) = \frac{\lambda_0}{\lambda_0 + \lambda_1 + \lambda_2}$$

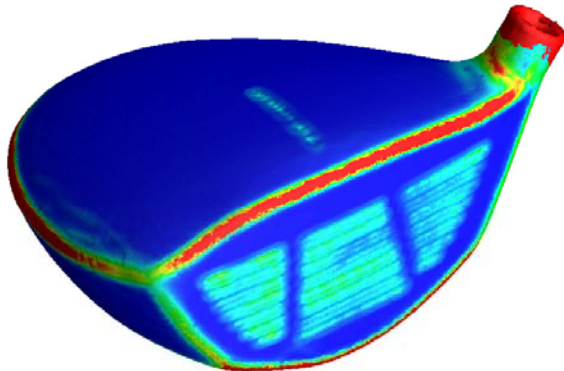
# Surface Variation



Input point cloud (200,000 points)

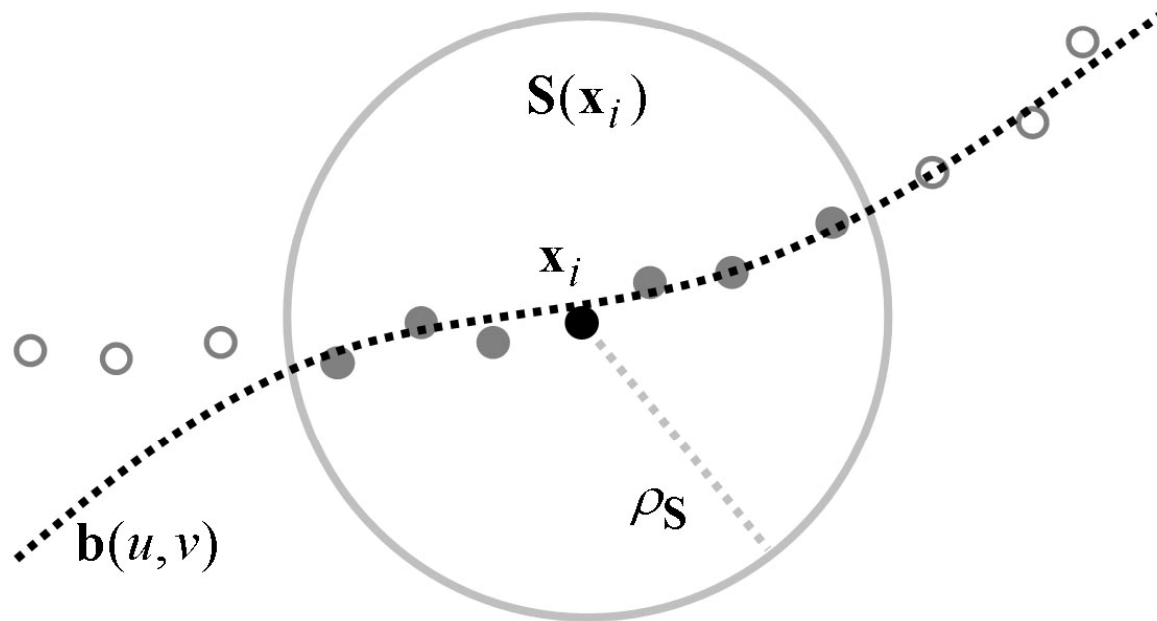


Surface variation using few nearest neighbors



Surface variation using many nearest neighbors

# Seed Regions



- If  $x_i$  has already been assigned to a region, skip it
- Otherwise, construct a seed region  $S(x_i)$  of all the unlabeled points within a radius  $\rho_S$  of  $x_i$

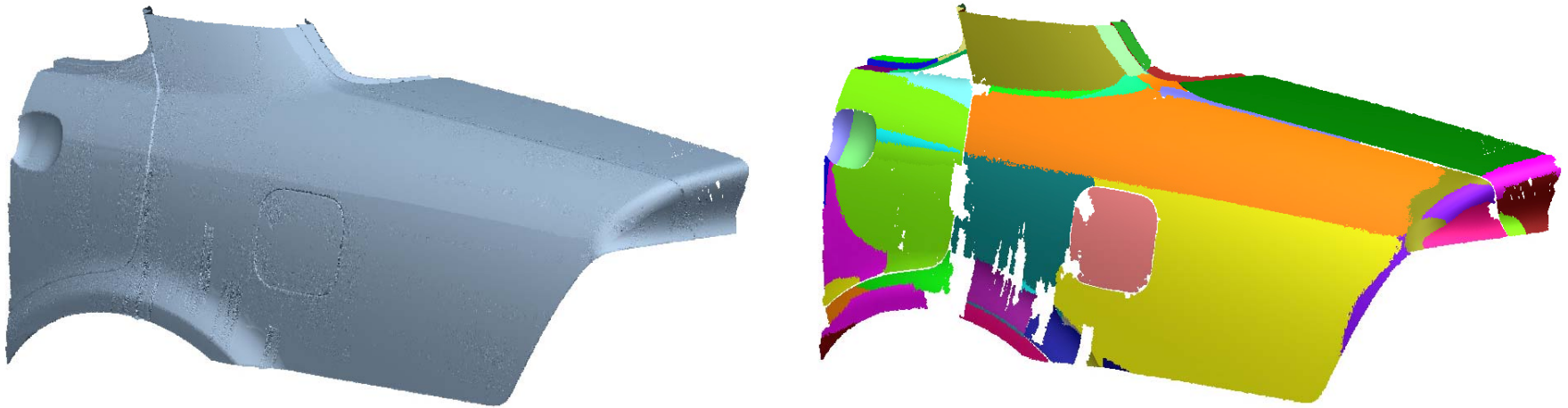
$$S(x_i) = \left\{ \mathbf{x} \in \mathbf{X} \mid \|\mathbf{x} - \mathbf{x}_i\| < \rho_S \text{ and } \mathbf{x} \text{ is unlabeled} \right\}$$

# Results

- We used a threshold distance of 0.3 mm
- Uses about 80 bytes per point, a fraction of the RAM required for processing a mesh
- Processes very large models in a few minutes

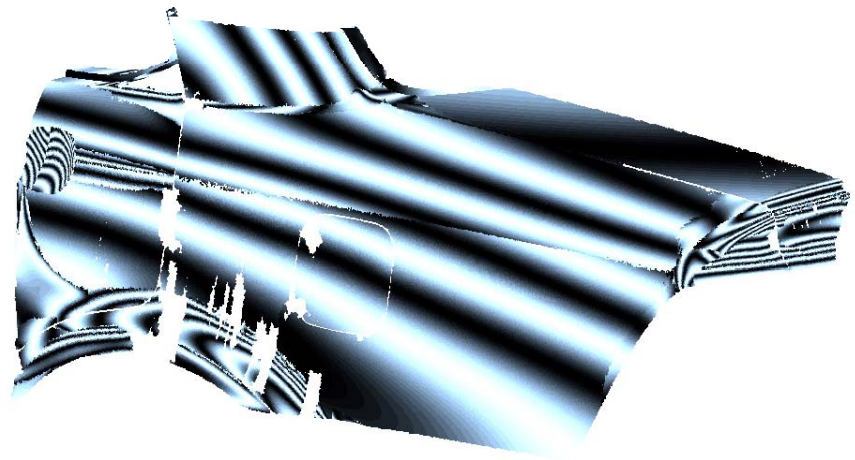
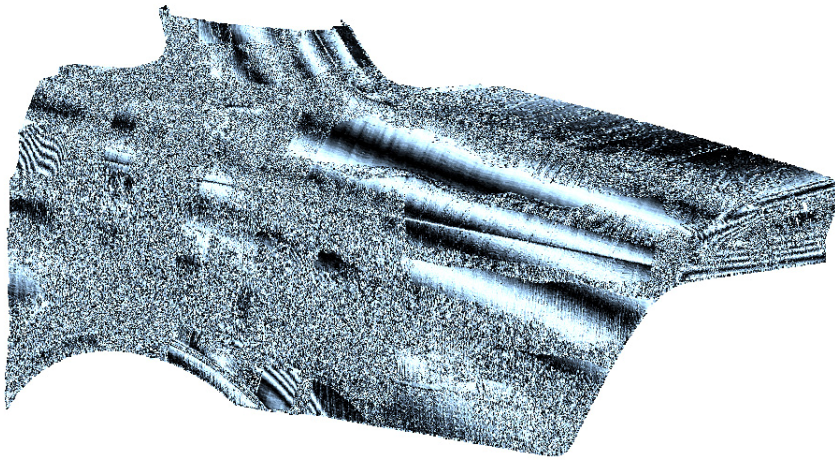
Model	Num. Points	Thresh. Angle	Peak RAM	Time (secs)
C-pillar	99,790	5°	25 MB	24
Golf Club	209,779	5°	33 MB	25
Rear Fender	1,065,886	6°	90 MB	255
Front Door	1,497,459	5°	125 MB	288

# Results – Rear Fender



- 1,065,886 points
- 90 MB peak RAM
- 255 secs

# Results – Rear Fender



- Simulated reflection lines on raw data and extracted surfaces

# Algorithms

- Mesh Smoothing
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- **Surface Reconstruction Proposal**
- Summary



# Motivation

- Can we blend and intersect the extracted surfaces?
- Can we create a piecewise-smooth reconstruction?
- The reconstructed model must:
  - Approximate the data to engineering tolerances
  - Be free of unnecessary undulations (principle of simplest shape)
  - Preserve sharp edges and character lines
- Reconstruction useful for: aesthetic interrogation, engineering analysis, manufacturing

# Proposed Work Outline

- Extract surfaces from point data
- Subdivide the object's bounding box into cells
- Find surface approximations in each cell
- Convert surfaces into an implicit representation
- Intersect surfaces at sharp edges
- Use the **Partition of Unity Method** to blend the approximations in each cell
- Reconstructed surface is the solution of a single implicit equation
- Established methods to polygonize the surface

# Related Work

- An implicit surface is the locus of 3D points such that  $F(\mathbf{x})=0$  for some scalar-valued function  $F(\mathbf{x})$
- Blending and intersecting surfaces becomes trivial [1]
- Used to create meshes from point clouds [2,3]:
  - Compute a signed distance function as the distance from each point to the tangent plane of the closest point in the point cloud
  - Extract the surface by meshing the zero level set of the signed distance function
- Implicit representations have also been used to create  $C^1$ -smooth reconstructions with B-splines [4]

[1] Bloomenthal. *Introduction to Implicit Surfaces*. Morgan Kaufmann Publishers, 1997.

[2] Hoppe, et al. *Piecewise Smooth Surface Reconstruction*, SIGGRAPH 94.

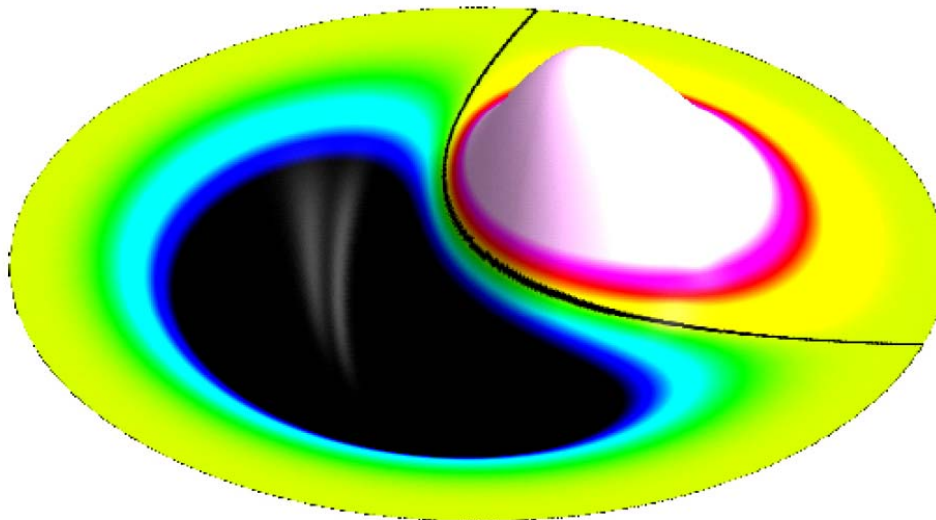
[3] Curless & Levoy. *A Volumetric Method for Building Complex Models from Range Images*, SIGGRAPH 96.

[4] Bajaj, et al. *Automatic Reconstruction of Surfaces and Scalar Fields from 3D Scans*, SIGGRAPH 95.

# Related Work - RBFs

- Approximate the points around various centers near the point cloud with a polynomial  $h(u,v)$  and set  $g_i(\mathbf{x})=w-h(u,v)$
- Sum the products of these local approximations with radial basis functions

$$f(\mathbf{x}) = \sum_i [g_i(\mathbf{x}) + \lambda_i] \phi_\sigma(\|\mathbf{x} - \mathbf{p}_i\|)$$



Ohtake, Y., Belyaev, A., and Seidel, H.-P. *A Multi-scale Approach to 3D Scattered Data Interpolation with Compactly Supported Basis Functions*. *Shape Modeling International 2003*, pp. 153-161.

# Related Work - PUM

- Partition of unity methods integrate locally defined approximations into a global approximation
  - Partition the global domain into small subdomains
  - Approximate the data in each subdomain
  - Blend the local solutions together with smooth weights that sum to one everywhere on the domain
- Originally developed to solve PDEs
- Used for computer graphics [1,2]
- Uses local representations that can be created and evaluated quickly

[1] Ohtake, et al. *Multi-Level Partition of Unity Implicits*, SIGGRAPH 2003.

[2] Tobor, et al. *Efficient Reconstruction of Large Scattered Geometric Datasets using the Partition of Unity and Radial Basis Functions*, WSCG 2004.

# Related Work Summary

- We need to blend and intersect extracted surfaces
  - Difficult to automate with explicit representation
  - Impossible with RBFs
- Methods developed for computer graphics ignore constraints of automotive styling design
- Can we use partition of unity methods to satisfy accuracy or geometric continuity constraints?
- How can we ensure that the surfaces and edges of the reconstructed object satisfy the principle of simplest shape?

# Partition of Unity Method

- On a bounded domain  $\Omega$ , we want a set of nonnegative functions  $\{\varphi_i\}$  with compact support such that

$$\sum_i \varphi_i = 1 \text{ on } \Omega$$

- Given a local approximation  $V_i(x)$  in each subdomain, the global approximation is

$$f(x) = \sum_i \varphi_i(x) V_i(x)$$

- Given a set of nonnegative compactly supported functions  $\{w_i(x)\}$  that cover the domain

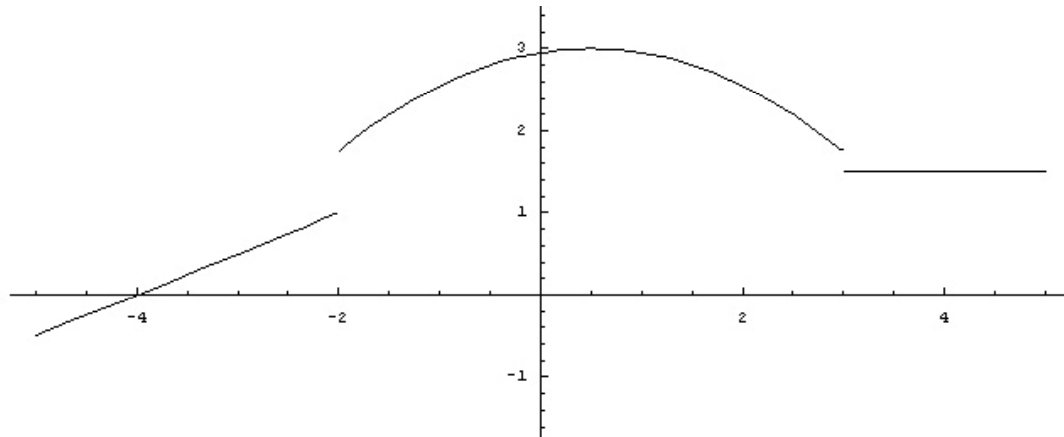
$$\Omega \subset \bigcup_i \text{supp}(w_i)$$

- This equation generates the partition of unity functions

$$\varphi_i(x) = \frac{w_i(x)}{\sum_j w_j(x)}$$

# PUM – 1D Example

- Consider three  $V_i(x)$  on the domain  $\Omega=(5,5)$

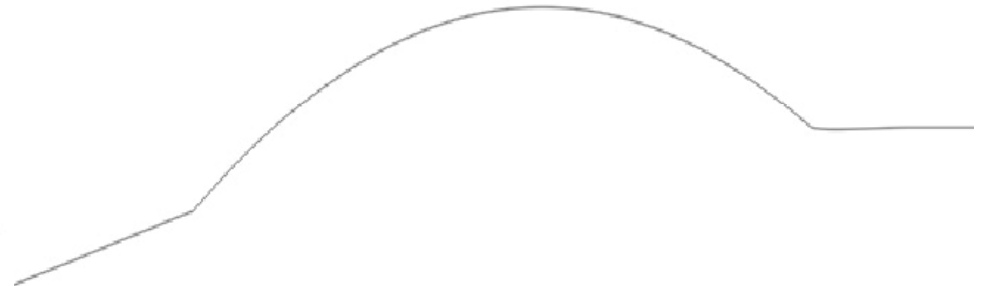
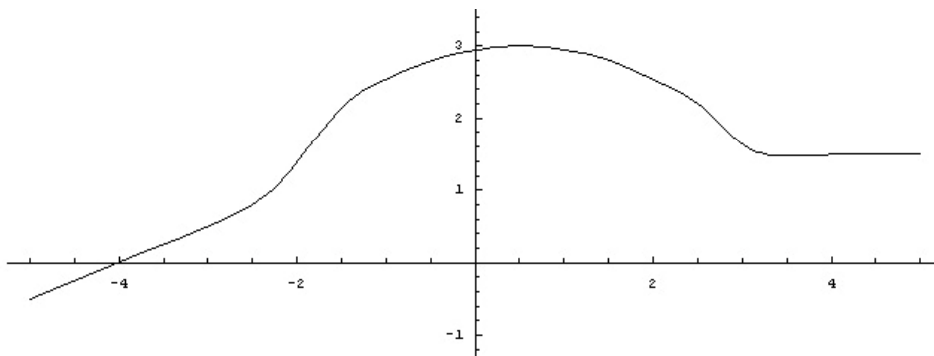


$$V_1(x) = \frac{x}{2} + 2 \quad \text{for } -5 < x < -2$$

$$V_2(x) = -\frac{1}{5} \left( x - \frac{1}{2} \right)^2 + 3 \quad \text{for } -2 < x < 3$$

$$V_3(x) = \frac{3}{2} \quad \text{for } 3 < x < 5,$$

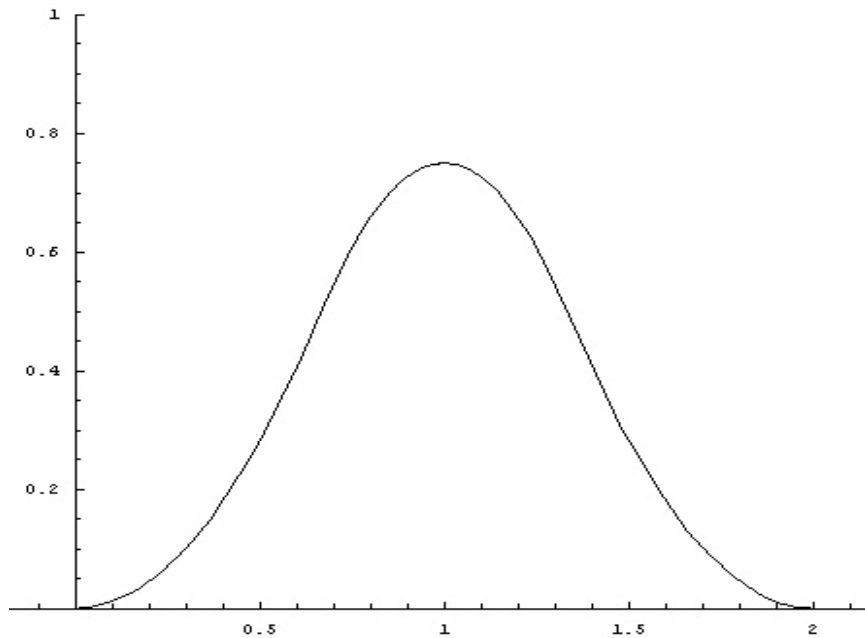
- How can we easily blend and intersect them?





# PUM – 1D Example

- The partition of unity functions  $\{\varphi_i\}$  are generated from the  $C^1$  function



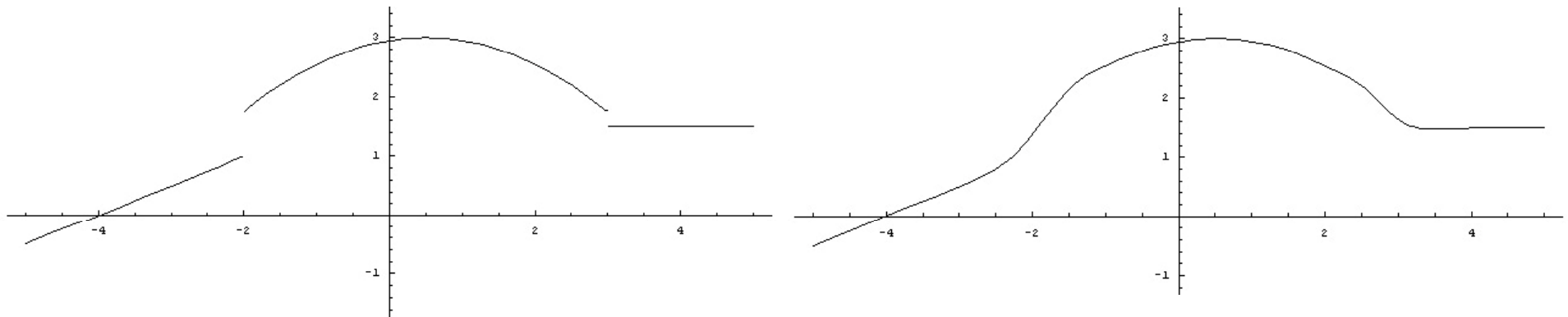
$$w(x, R) = \begin{cases} \frac{9}{8} \frac{x^2}{R^2} + \frac{9}{4} \frac{x}{R} + \frac{9}{8} & \text{for } -R \leq x < -\frac{R}{3} \\ -\frac{9}{4} \frac{x^2}{R^2} + \frac{3}{4} & \text{for } -\frac{R}{3} \leq x < \frac{R}{3} \\ \frac{9}{8} \frac{x^2}{R^2} - \frac{9}{4} \frac{x}{R} + \frac{9}{8} & \text{for } \frac{R}{3} \leq x < R. \end{cases}$$

- We can use any positive functions with compact support
- The reconstruction inherits the continuity of the  $\{\varphi_i\}$

# PUM – 1D Example

- The blended global approximation is simply

$$f(x) = \frac{w_1 V_1 + w_2 V_2 + w_3 V_3}{w_1 + w_2 + w_3}$$

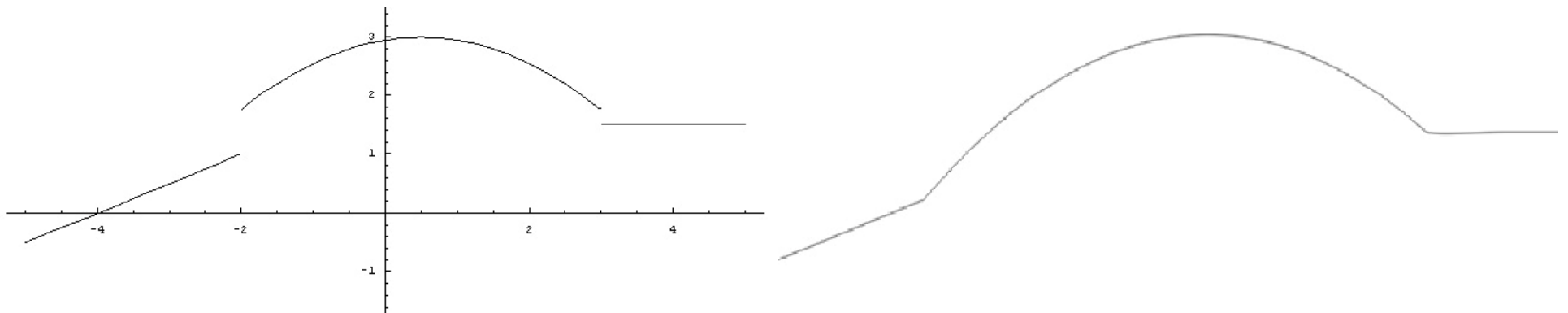


- We can control the strength of the blending by changing the parameter  $R$  of the  $w_i(x, R)$

# PUM – Implicit 1D Example

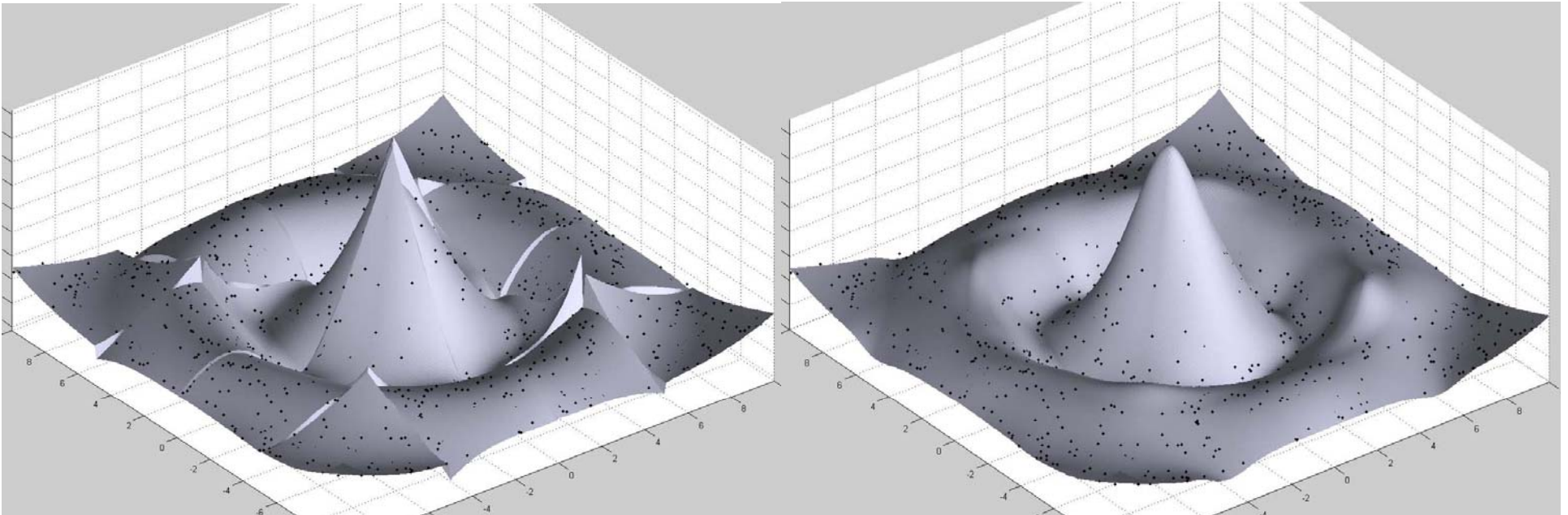
- Replace the  $V_i(x)$  with  $y-V_i(x)$  to define the blended function implicitly
- Now it's trivial to intersect the functions

$$\frac{\min[w_1(y - V_1), w_1(y - V_2)] + w_2(y - V_2) + \min[w_3(y - V_2), w_3(y - V_3)]}{w_1 + w_2 + w_3} = 0$$



# PUM – 2D Example

- These ideas extend to 2- and 3-dimensions

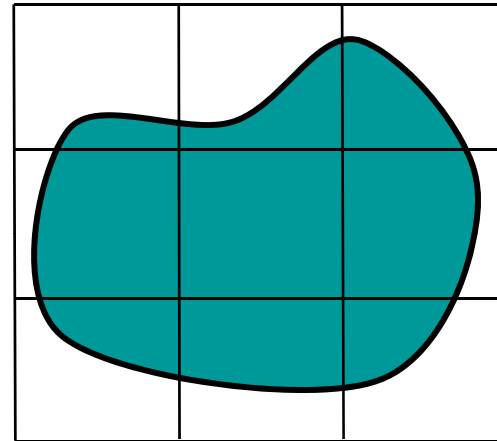
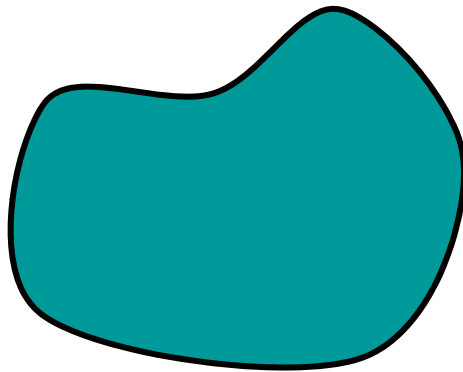


- 16 cubic surfaces approximating synthetic noisy data

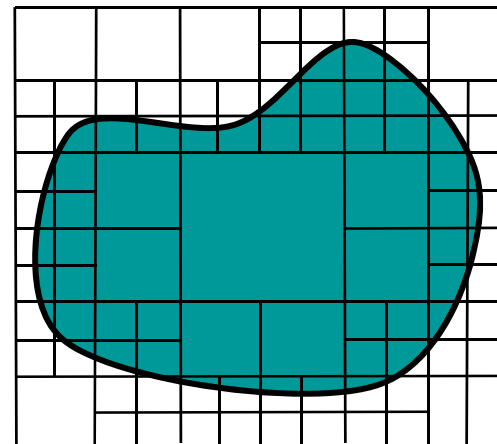
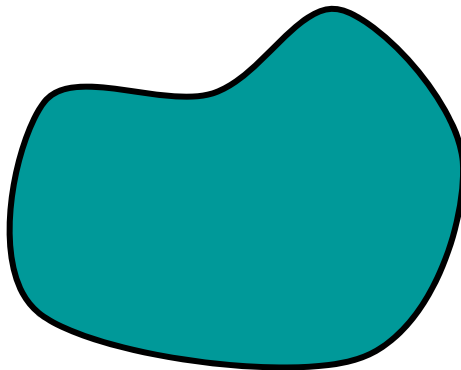
- $C^2$  blend of the 16 surfaces

# Proposed Research – Domain Subdivision

- First step is to subdivide the domain into small cells
- Cubical Grid

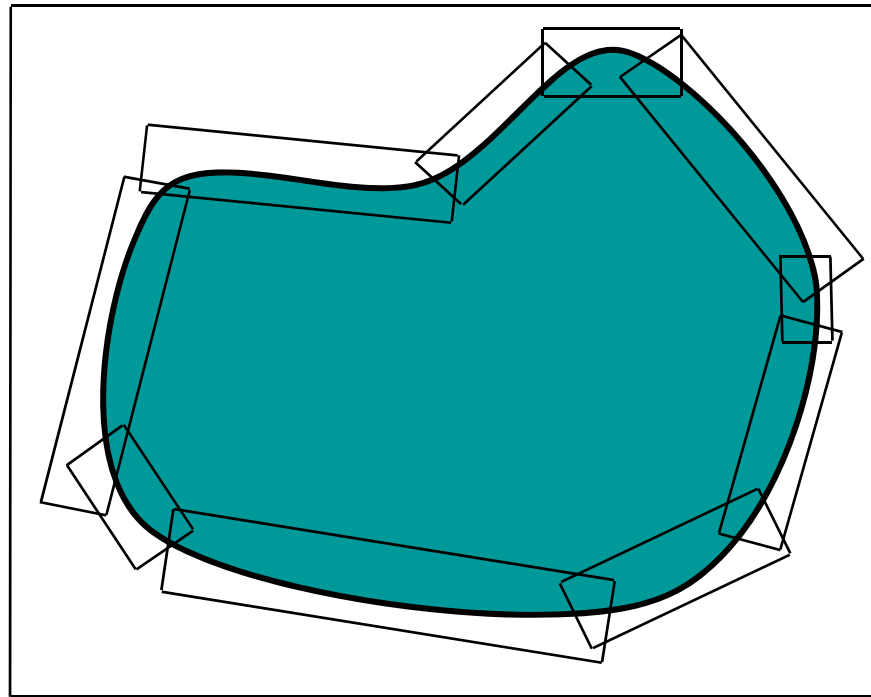


- Octree Subdivision



# Proposed Research – Domain Subdivision

- Geometry-adaptive cells
  - Quality of the reconstructed surface varies with the size and orientation of the subdivision cells
  - We can use local geometry information to determine the size and orientation of the cells on the point cloud

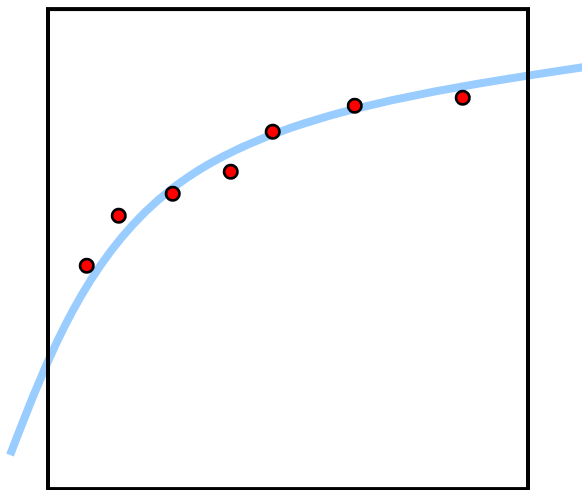


# Proposed Research – Domain Subdivision

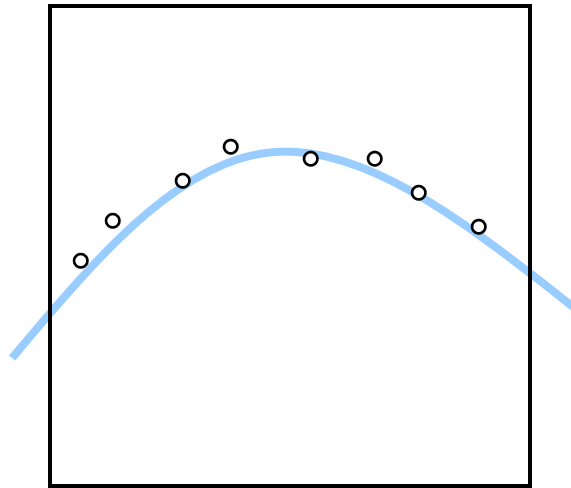
- Questions we will address:
  - Can we make cells that vary in size and orientation according to the object geometry?
  - How do we ensure the cells overlap?
  - How do we integrate them with the rest of the domain?
  - Will the computational cost and difficulty of finding the geometry-adaptive cells be justified by the improved quality of the reconstruction?

# Proposed Research – Local Approximations

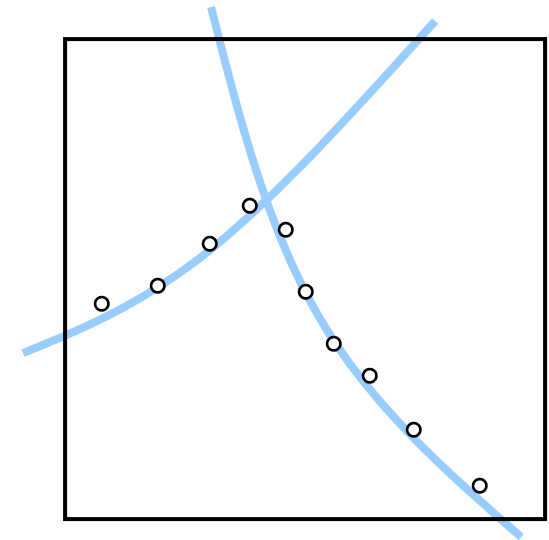
- Then we use the following information to determine the local approximations in each cell
  - Does it contain less than a certain number of points?
  - How many extracted surfaces are defined inside it?
  - Does it contain a sharp edge or corner?



Points already segmented



Points not segmented



Sharp edge detected



# Proposed Research – Local Approximations

- Questions we will address:
  - How can we integrate geometry-adaptive cells with this approach?
  - What recursive subdivision rules will give the best results?
  - How will we deal with outlier noise?
  - How reliably can we detect sharp edges or corners and fit separate surfaces to the points around them?

# Proposed Research – Isosurface Extraction

- The reconstructed surface is the zero level set of a signed distance function
- Extract isosurfaces from implicit functions
- Convert the approximation in each cell to implicit forms
- Multiply the approximations by the partition of unity functions and sum them over the domain
- For cells that do not contain points, we can estimate the signed distance function by finding the nearest point to the cell and examining its normal

# Algorithms

- Mesh Smoothing
- Surface Extraction from Meshes
- Surface Extraction from Point-Sampled Data
- Surface Reconstruction Proposal
- **Summary**

# Expected Contributions

- Mesh Smoothing
  - Creates an aesthetically pleasing surface
  - Minimizes mesh deformation
  - Preserves sharp edges
- Surface Extraction
  - Estimates curvatures and noise levels on the data
  - Detects sharp edges
  - Segments data into regions approximated by single surfaces
  - Fits surfaces to a specified tolerance
- Surface Reconstruction (proposed)
  - Will reconstruct objects with large, smooth surfaces, smooth blends between surfaces, and sharp edges
  - Will bound the accuracy and geometric continuity of the reconstructed object

# Publications

- Mesh Smoothing

- M. Vieira, K. Shimada, and T. Furuhashi. *Local Least Squares Fitting for Surface Mesh Fairing in Automobile Panel Design*, ASME DETC / DAC. 2002, Montreal, Canada.
- M. Vieira, K. Shimada, and T. Furuhashi. *Smoothing of Noisy Laser Scanner Generated Meshes Using Polynomial Fitting and Neighborhood Erosion*, ASME Journal of Mechanical Design, May 2004.

- Surface Extraction

- M. Vieira, K. Shimada. *Segmentation of Noisy Laser-Scanner Generated Meshes With Piecewise Polynomial Approximations*, ASME DETC / DAC. 2004, Salt Lake City, Utah. (Winner DAC Best Paper Award)
- M. Vieira, K. Shimada. *Surface Mesh Segmentation and Smooth Surface Extraction Through Region Growing*, Computer Aided Geometric Design Journal, (accepted; submitted July 2004).
- M. Vieira, K. Shimada. *Surface Extraction from Point-Sampled Data through Region Growing*, International Journal of CAD/CAM, (submitted).