Registration of Deformable Objects





Christopher DeCoro

Includes content from: Consistent Mesh Parameterizations, Praun et. al, Siggraph 2001 The Space of Human Body Shapes, Allen et. al, Siggraph 2003 Shape-based 3D Surface Correspondence Using Geodesics and Local Geometry, Wang et al, CVPR 2000

Talk outline

- Introduction
 - Definition
 - Motivation
- Consistent Mesh Parameterization
- · Parameterization of Human Body Shapes
- Surface Correspondence Using Geodesics and Local Geometry
- Conclusion



Definition

- What is Deformable Body Registration?
- Establishing 1 to 1 mapping between points on one model, and corresponding points on a similar, but deformed, model
- Example: Texture Transfer
 - The male human, female human, and horse models have parts in correspondence, and texture coords can be shared





Motivation – Digital Geometry Processing

- · Surface do not have simple parameterization, as do images
 - Images are in Euclidean space
 - Images are regularly sampled
 - Mesh Surfaces are neither
- Registration provides consistent parameterization
 - Allows for basic operations like mean
 - More complex signal processing





Motivation - Morphing



- · Would like to smoothly transition from one model to another
- · When registered, simply use linear combinations of vertices



Motivation – Attribute Transfer

- Copy surface attributes from one surface to another
 - Texture transfer (as shown previously)
 - Deformation weight transfer (below)
 - Segmentation transfer





Motivation – Correct Hole Filling



- · Models captured through range scanning have holes
- Smooth hole filling produces artifacts in flat regions
 Such as the soles of the feet
- · Reparameterization allows for correct behavior

Motivation – Medical Analysis

- · Would like to identify common features
 - Most organs do not differ greatly from person to person
 - In brains, we see homothetic deformation (local uniform stretch)
- · Can use domain-specific knowledge to guide registration





Talk outline

- Introduction
- Consistent Mesh Parameterization
 - Purpose and Problem Specification
 - Topologically Equivalent Nets
 - Restricted Brush Fire Algorithm
 - Fair Boundary Curves & Heuristics
- · Parameterization of Human Body Shapes
- Surface Correspondence Using Geodesics and Local Geometry
- Conclusion



Purpose and Problem Specification

- Algorithm Input
 - Set of meshes S
 - Feature points F defined on each mesh M
- Algorithm Goal
 - Determine common base domain B and connectivity $L_{0} \label{eq:L0}$
 - Remesh each M with base domain B
 - Create fair patch boundaries equivalent to L₀





Topologically Equivalent Nets

- Definition: A **patch** is a region of semi-regular connectivity in which triangles correspond to a single triangle in B
- Definition: A net is the outline of patch boundaries
- We want a net that matches the connectivity L0
 - Two patch boundaries may only intersect at a feature vertex
 - Each feature vertex has a consistent cyclical ordering of edges
 - Patch boundaries may not intersect
- · Naïve algorithm (shortest path) does not achieve this





- Standard Brush Fire
 - Starts fire at vertex
 - Fire expands uniformly until it hits other vertex
 - That is the shortest path
- Restricted Brush Fire
 - Uses existing paths as firewalls
 - Will only connect to vertex if approached from correct ordering



- Must avoid blocking off vertices
- Avoid completing any cycle until spanning tree of L0 traced



Fair Boundary Curves

- Rather than simply accept topologically equivalent net, we would like certain properties
 - Equal distribution of surface area between patches
 - Smooth Patch Boundaries
 - Fair patch boundaries (should not swirl)



- First two can be handled using relaxation
 - Iterative technique that involves progressively improving curve
- · Third requires optimization of complicated expression
 - Intractable, so try heuristics



- Parameterization
 - Construct parameterization from base mesh to target
- Tracing Curves
 - Construct objective function that makes curves repel each other
- Priority Queues
 - Use a priority queue to control validity testing
- Swirl Detection
 - Trace a line to detect swirl crossings
- Curve Straightening
 - Allow curves to pass through center of triangles



Talk outline

- Introduction
- Consistent Mesh Parameterization
- · Parameterization of Human Body Shapes
 - Problem Specification
 - Optimization Variables
 - Objective Function
 - Algorithm Procedure
 - Feature Analysis
 - Markerless Matching
- Surface Correspondence Using Geodesics and Local Geometry



Problem Specification

- Algorithm Input
 - Set of human range images
 - » All in similar poses
 - Set of colored feature markers
- Algorithm Goal
 - Develop correspondence from template to target
 - Compute affine transform for each vertex
 - Minimize error function



Optimization Variables

- · Algorithm viewed as optimization problem
 - Given an initial template surface with vertices v_i
 - Corresponding affine transformation matrices T_i
 - Current state is $T_i v_i$ for all i (see diagram)
 - Find values of T_i to minimize objective function
 - Attempts to find a "good fit" (blue) of template (cyan) to target (red)



Objective Function

- Objective Function has three weighted terms
 - Data error
 - Smoothness error
 - Marker error

$$E = \alpha E_d + \beta E_s + \gamma E_m$$

Will use different weights in each phase of process
 – Multistep / Multi-resolution fitting process



Objective Function – Data Error

- Data Error term requires current match to be close to target
 - Uses distance from each transformed vertex to the target surface
 - Weighted by confidence measure (from scanning)
 - Hole regions have weight = 0

Sums total error

$$E_d = \sum_{i=1}^n w_i \operatorname{dist}^2(\mathbf{T}_i \mathbf{v}_i, \mathcal{D})$$

- Distance function
 - Uses transformed template vertex
 - Takes minimum distance to "compatible" vertices in target
 - Compatible defined as those with normal w/in 90 deg.

Objective Function – Smoothness Error

- · Measures smoothness of deformation applied to template
 - Problem is under-constrained using data error
 - E_s measures change in T_I between adjacent vertices
 - Encourages similarly-shaped features to be mapped to each other

$$E_{s} = \sum_{\{i,j|\{\mathbf{v}_{i},\mathbf{v}_{j}\} \in edges(\mathcal{T})\}} ||\mathbf{T}_{i} - \mathbf{T}_{j}||_{F}^{2}$$

- Uses Frobenius norm (vector L2 norm)





Objective Function – Marker Error

- Data and Smoothness Error can hit local minima

 Example: left arm transformed to right arm
- Solution: Use pre-labeled markers on the test subjects
 - Viewed as white dots in the range image
 - Correspondences set up beforehand (as in Consistent Mesh Parameterization)
 - 74 markers per subject (not all are used, however)
- · Measure distance from template marker to target marker
 - K_I are the indices of the markers in template, m_I are target markers

$$E_m = \sum_{i=1}^m ||\mathbf{T}_{\kappa_i} \mathbf{v}_{\kappa_i} - \mathbf{m}_i||^2$$



Algorithm Procedure

Minimize error function using L-BFGS-B algorithm
 – Quasi-Newton method with limited memory usage

$$E = \alpha E_d + \beta E_s + \gamma E_m$$

- Make four passes over data (2 low res, 2 high res)
 - Fit markers (low res, $\alpha = 0$, $\beta = 1$, $\gamma = 10$)
 - Refit using data term (low res, $\alpha = 1$, $\beta = 1$, $\gamma = 10$)
 - Repeat in high resolution (hi res, $\alpha = 1$, $\beta = 1$, $\gamma = 10$)
 - Refit using predominantly data term (hi res, α = 10, β = 1, γ = 1)



Markerless / Marker-only Matching

- Using PCA, we can remove the marker requirement
 - A set of training data is fit using markers
 - Other data can be registered using unmarked range scans
 - Uses PCA weights to search PCA space, not transformation space
- · Also, we can use PCA to remove the range images
 - Only use markers; can be captured with much cheaper equipment
 - Allows us to determine approximate shape of object





Talk outline

- Introduction
- Consistent Mesh Parameterization
- · Parameterization of Human Body Shapes
- Surface Correspondence Using Geodesics and Local Geometry
 - Problem Specification
 - Objective Function
 - Feature Match Measure
 - Correspondence Interpolation
- Conclusion



Problem Specification

- Algorithm Input
 - Set of human brain volumes (triangulated w/ Marching Cubes)
 - Prelabeled reference brain mesh (low resolution)
- Algorithm Goal
 - Develop correspondence from template to target (as before)
 - Identify particular features in the brain (gyri, sulci)
 - Minimize error function



Objective Function

- Minimizes error between vertex and feature point $O_{ij} = d_{ij} \cdot n_{ij} \cdot f_{ij}$
- Euclidean distance measure

$$d_{ij} = 1 + \sqrt{[x_i - x_j]^2 + [y_i - y_j]^2 + [z_i - z_j]^2}$$

- Surface Normal Match $n_{ij} = 2 - \vec{n}_i \cdot \vec{n}_j$



Feature Match Measure

- · Domain-specific measurement based on brain features
- Determined by measuring curvature
 Compute Mean curvature and Gaussian curvature

$$\begin{split} K &= \frac{\sum_{(i,j,k)\in\Omega} \left[\begin{array}{c} L_i^2(L_{jj}L_{kk} - L_{jk}^2) \\ +2L_iL_j(L_{ik}L_{jk} - L_{ij}L_{kk}) \end{array} \right]}{(L_i^2 + L_j^2 + L_k^2)^2} \\ H &= \frac{\sum_{(i,j,k)\in\Omega} \left[(L_{ii} + L_{jj})L_k^2 - 2L_iL_jL_{ij} \right]}{2(L_i^2 + L_j^2 + L_k^2)^{3/2}} \end{split}$$

- Compute principle curvatures k1 = H + sqrt(H² K); k2 = H sqrt(H²-K)
- Compute Shape Index Function S = 2/PI * arctan[(k2 + k1) / (k2 k1)]
- Compute Signed Curvedness

$$C_s = \begin{cases} \sqrt{\frac{k_1^2 + k_2^2}{2}}, & \text{if } S \ge 0\\ -\sqrt{\frac{k_1^2 + k_2^2}{2}}, & \text{if } S < 0 \end{cases}$$

- Halfway there!

Feature Match Measure (2)

- We now use curvedness to estimate feature type
 Gyrus is a ridge in the brain
 - Sulcus is a crease in the brain

$$t = \begin{cases} \text{gyrus,} & \text{if } C_s > K_g \\ \text{sulcus,} & \text{if } C_s < -K_s \\ \text{no feature,} & \text{otherwise} \end{cases}$$

- Adjust the Kg and Ks to get a certain percentage of feature points
- Use labeling of points in template brain to compute scale

scale =
$$\begin{cases} 1, & \text{if } l = 3 \text{ or } 4 \\ 2, & \text{if } l = 1 \\ 3, & \text{if } l = 2 \end{cases}$$

- Type 1 = interhemispheric fissure sulcal points; Type 2 = brain stem crease
- Type 3 = other sulcal points; Type 4 = gyral points



- Almost there!

Feature Match Measure (3)

Finally, we use all this information to compute feature measure

$$f_{ij} = \begin{cases} 1.0, & \text{if } (t_i, t_j) = \begin{cases} (\text{sulcus, sulcus}) \\ (\text{gyrus, gyrus}) \\ (\text{no feature, no feature}) \\ (\text{sulcus, no feature}) \\ 3.0, & \text{if } (t_i, t_j) = (\text{sulcus, gyrus}) \end{cases}$$

- Assign correspondence to point that minimizes error func.
 - In this paper, perform exhaustive search in 15-voxel radius



Correspondence Interpolation

- Given mapping to feature points, map intermediate points
 Same idea as in Consistent Mesh Parameterization
- Trace geodesic path
 - Between vertices that are connected in template mesh
 - Use Fast Marching Method for finding curves
- Subdivide patches
 - Insert additional vertices at midpoints of geodesic paths
 - This produces higher resolution mesh
 - Template mesh begins to approximate target mesh
- Repeat
 - Process is repeated to iterative improve correspondence
 - Example given of 4 iterations



Conclusion

- Progress needs to be made in initializing registration
 - All require correspondences to be initially pre-selected
 - One can use PCA to avoid features after training
 - Future work might use local shape descriptors
 - » Would have to be robust against misplaced feature points
 - This would allow for use in search and retrieval
- Results with initial features are quite good
 Allows for wide variety of applications
- Related Project Ideas
 - Monkey Skulls Create correspondence
 - Brain registration using distance over surface

