

# Non-Rigid Range-Scan Alignment Using Thin-Plate Splines

Benedict J. Brown   Szymon Rusinkiewicz

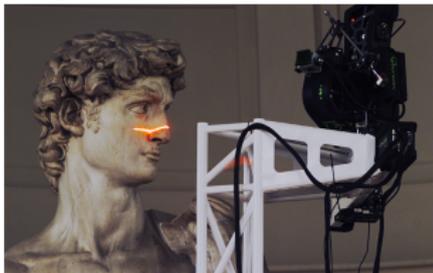
Princeton University

`{bjbrown, smr}@cs.princeton.edu`

9 September 2004

# Some Large Scanning Projects

## Digital Michelangelo



Stanford Graphics Group

## Forma Urbis Romae



Stanford Graphics Group

## Great Buddha



CVL, University of Tokyo

## Florentine Pietà



IBM Research

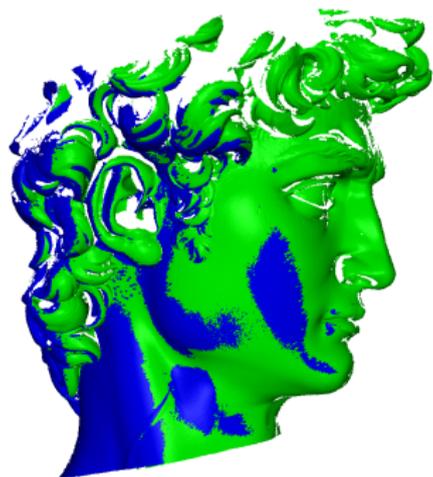
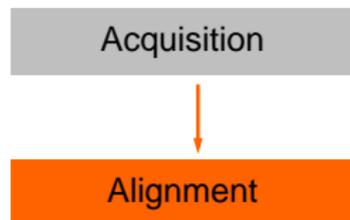
# Range Scanning Pipeline

## Acquisition

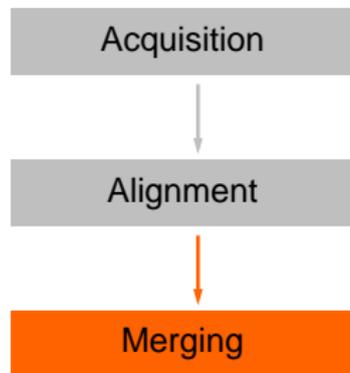
- ▶ Scanners acquire data from a single viewpoint



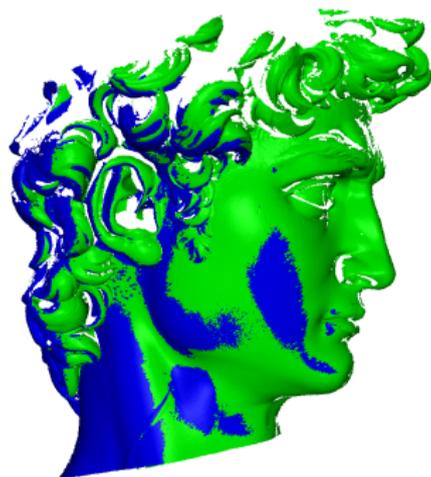
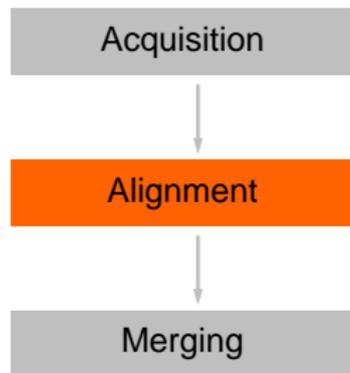
# Range Scanning Pipeline



# Range Scanning Pipeline

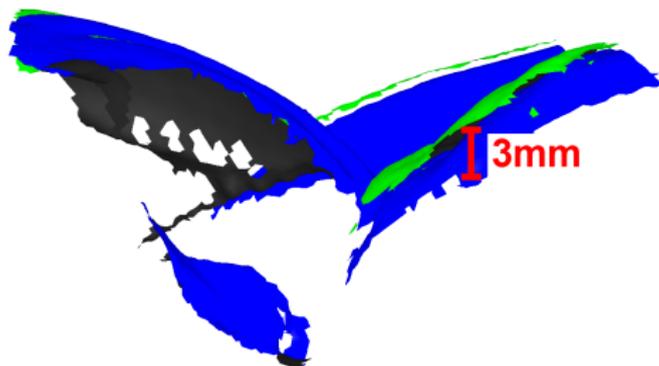
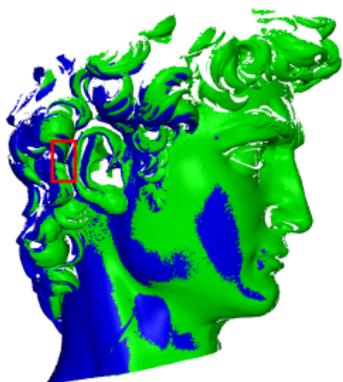


# Range Scanning Pipeline



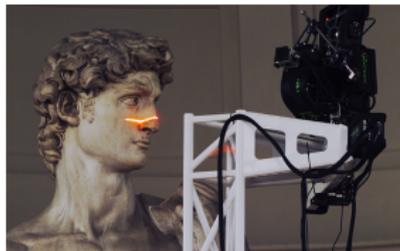
# Alignment Problems

- ▶ Existing alignment algorithms fail
- ▶ Non-rigid calibration error



# Digital Michelangelo Project [Levoy00]

- ▶ Scan Michelangelo's statues in Florence using a laser range finder
- ▶ .25mm precision over entire statue
- ▶ David is 5m high
- ▶ Gantry is 7.6m high
- ▶ Extreme requirements cause unavoidable calibration errors



Paul Debevec



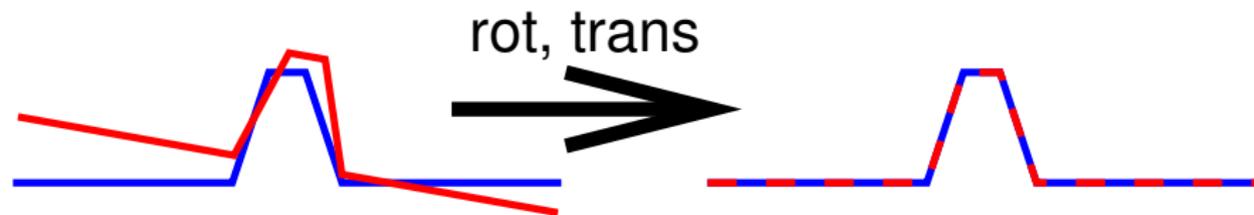
Stanford Graphics Group

# Overview

- ▶ Previous Work
  - ▶ Iterative Closest Points (Rigid-Body Alignment)
  - ▶ Hierarchical ICP
- ▶ Non-Rigid Alignment
  - ▶ Thin-Plate Splines
- ▶ Feature Correspondences
  - ▶ Piecewise ICP
- ▶ Pairwise Non-Rigid Alignment
- ▶ Results & Future Work

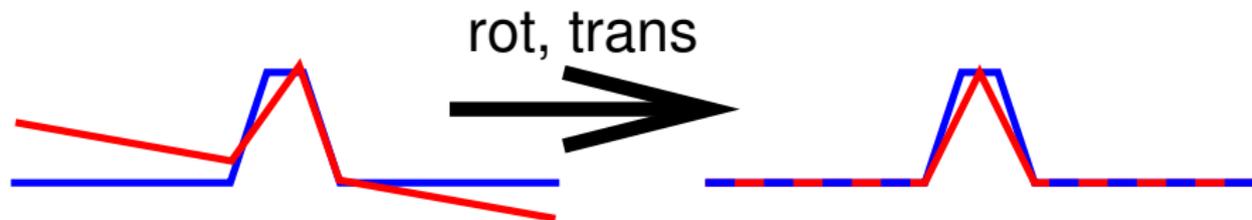
# Rigid-Body Alignment

- ▶ Range scans are of a single, rigid object
  - ▶ Rigid-body transformation should yield exact alignment



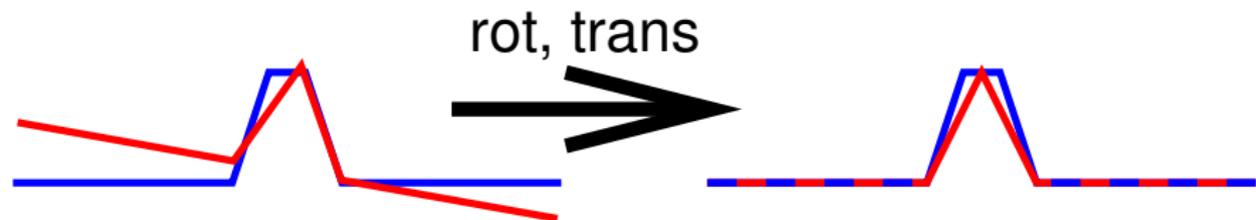
# Rigid-Body Alignment

- ▶ Range scans are of a single, rigid object
  - ▶ Rigid-body transformation should yield exact alignment
- ▶ Not possible even with a perfectly calibrated camera
  - ▶ Noise and irregular sampling



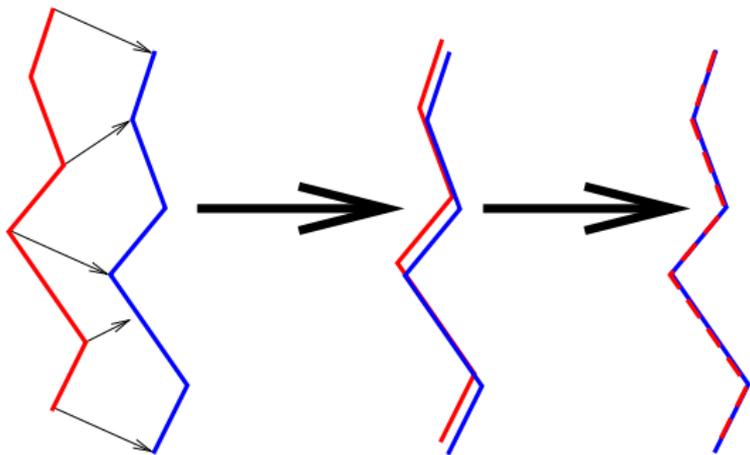
# Rigid-Body Alignment

- ▶ Range scans are of a single, rigid object
  - ▶ Rigid-body transformation should yield exact alignment
- ▶ Not possible even with a perfectly calibrated camera
  - ▶ Noise and irregular sampling
- ▶ Instead find least squares fit



## Iterative Closest Points [Besl92]

- ▶ To fit two meshes, need correspondence between points
  - ▶ Assume points correspond to closest points on other mesh
  - ▶ Compute best fit on a subset of all points
- ▶ If starting point was good, result should be better
  - ▶ Iterate until fit converges to minimum error



# Advantages of ICP

- ▶ Efficient (seconds per pair of meshes)

# Advantages of ICP

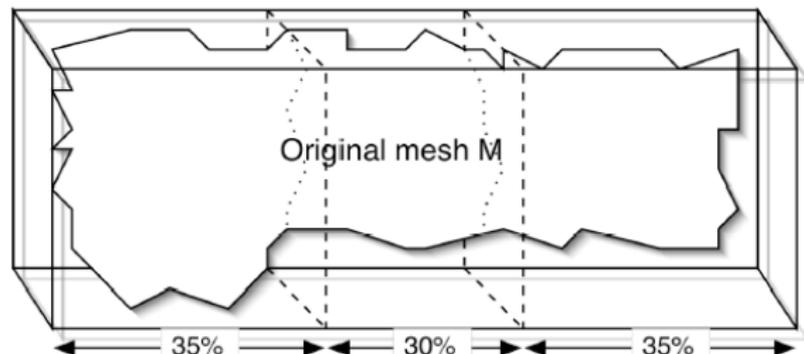
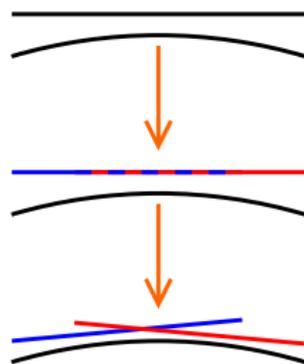
- ▶ Efficient (seconds per pair of meshes)
- ▶ Robust and stable, especially with advanced sampling
  - ▶ Select samples which constrain ICP [Gelfand03]
  - ▶ Sample features heavily

# Advantages of ICP

- ▶ Efficient (seconds per pair of meshes)
- ▶ Robust and stable, especially with advanced sampling
  - ▶ Select samples which constrain ICP [Gelfand03]
  - ▶ Sample features heavily
- ▶ Instead of point-to-point distance, use point-to-plane [Chen92]
  - ▶ Features lock onto each other, while flat areas can slide freely
  - ▶ Convergence is both more stable and faster

# Hierarchical ICP [Ikemoto03]

- ▶ Dice meshes into small pieces
  - ▶ Do global alignment on all pieces
- ▶ Neighboring pieces must contain some overlap
  - ▶ Too little overlap leads to discontinuities
  - ▶ Too much overlap prevents freedom in warping
- ▶ Not smooth, slow (hours per alignment)



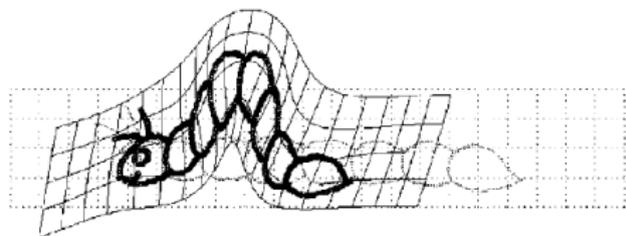
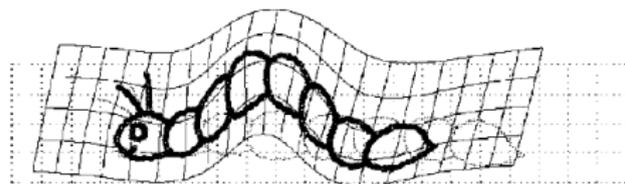
Ikemoto *et al.*

# Overview

- ▶ Previous Work
  - ▶ Iterative Closest Points (Rigid-Body Alignment)
  - ▶ Hierarchical ICP
- ▶ Non-Rigid Alignment
  - ▶ Thin-Plate Splines
- ▶ Feature Correspondences
  - ▶ Piecewise ICP
- ▶ Pairwise Non-Rigid Alignment
- ▶ Results & Future Work

# Non-Rigid Alignment

- ▶ Calibration error is
  - ▶ low-frequency  $\Rightarrow$  smooth, slowly-varying function
  - ▶ hard to characterize, so need flexible function
- ▶ Use non-rigid warp to compensate for calibration error
- ▶ Represent with thin-plate splines [Bookstein89] [Wahba90]



Chui & Rangarajan

# Thin-Plate Splines

- ▶ Maps source point set  $X$  to target set  $Y$ :  $f(x_i) = y_i$

# Thin-Plate Splines

- ▶ Maps source point set  $X$  to target set  $Y$ :  $f(x_i) = y_i$
- ▶ Minimizes *bending energy*:

$$J = \iiint f_{xx}^2 + f_{yy}^2 + f_{zz}^2 + 2(f_{xy}^2 + f_{yz}^2 + f_{zx}^2) \, dx \, dy \, dz$$

# Thin-Plate Splines

- ▶ Maps source point set  $X$  to target set  $Y$ :  $f(x_i) = y_i$
- ▶ Minimizes *bending energy*:

$$J = \iiint f_{xx}^2 + f_{yy}^2 + f_{zz}^2 + 2(f_{xy}^2 + f_{yz}^2 + f_{zx}^2) \, dx \, dy \, dz$$

- ▶ Gives the “minimal” deformation from an affine transformation necessary to map  $X$  onto  $Y$

# Thin-Plate Splines

- ▶ Maps source point set  $X$  to target set  $Y$ :  $f(x_i) = y_i$
- ▶ Minimizes *bending energy*:

$$J = \iiint f_{xx}^2 + f_{yy}^2 + f_{zz}^2 + 2(f_{xy}^2 + f_{yz}^2 + f_{zx}^2) \, dx \, dy \, dz$$

- ▶ Gives the “minimal” deformation from an affine transformation necessary to map  $X$  onto  $Y$
- ▶ Calculate by minimizing energy functional

$$E_{TPS} = \sum_{i=1}^n |y_i - f(x_i)|^2 + n\lambda J$$

for a fixed  $\lambda$ .

# Thin-Plate Splines

$$E_{TPS} = \sum_{i=1}^n |y_i - f(x_i)|^2 + n\lambda J$$

- ▶ Interpolates control points while minimizing warp
  - ▶ Reduces to affine transformation when that is sufficient
- ▶  $E_{TPS}$  is minimized by a linear system of equations
- ▶  $\lambda$  provides tradeoff of warp smoothness and interpolation
  - ▶  $\lambda$  corresponds to the measurement variance
  - ▶ To achieve good alignment, we must have low variance
    - ▶  $\Rightarrow \lambda \approx 0$

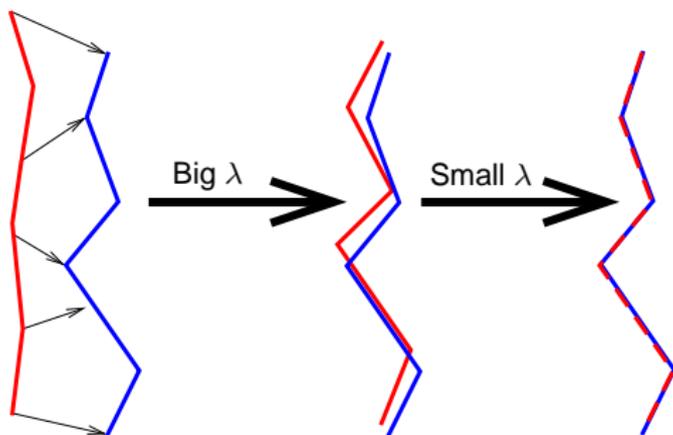
# Overview

- ▶ Previous Work
  - ▶ Iterative Closest Points (Rigid-Body Alignment)
  - ▶ Hierarchical ICP
- ▶ Non-Rigid Alignment
  - ▶ Thin-Plate Splines
- ▶ Feature Correspondences
  - ▶ Piecewise ICP
- ▶ Pairwise Non-Rigid Alignment
- ▶ Results & Future Work

# Finding Correspondences for TPS

Thin-plate splines can interpolate their control points exactly, regardless of the amount of warp, so iterative correspondences don't work.

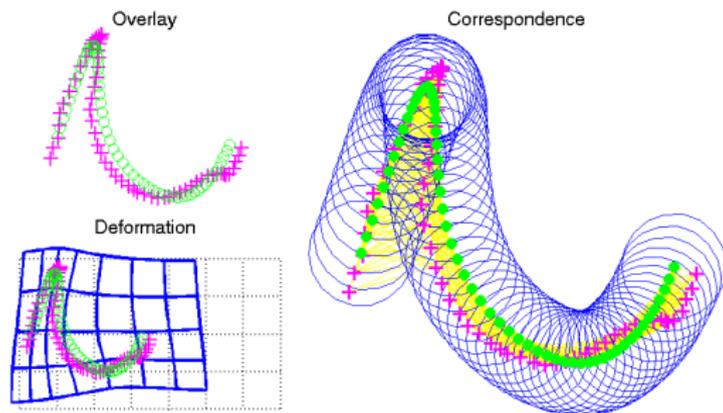
- ▶ Progressively anneal  $\lambda$



# Finding Correspondences for TPS

Thin-plate splines can interpolate their control points exactly, regardless of the amount of warp, so iterative correspondences don't work.

- ▶ Progressively anneal  $\lambda$
- ▶ Fuzzy correspondences [Chui03]



Chui & Rangarajan

# Piecewise ICP

- ▶ Record ICP alignment errors for each piece
- ▶ Dice piece with highest error
- ▶ Stop when alignment becomes unstable



Target scan



Diced source scan



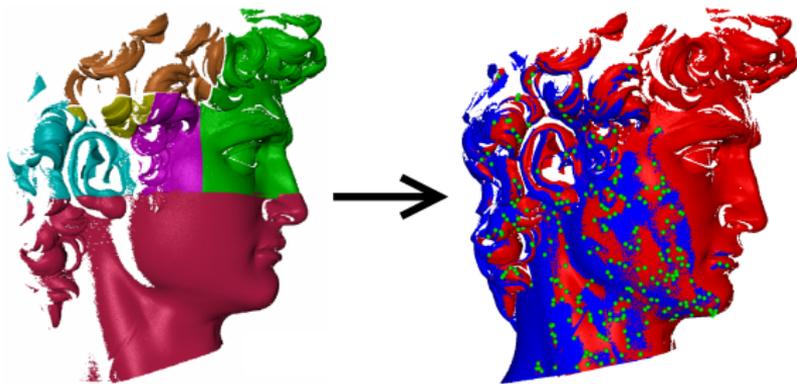
# Pairwise Alignment Pipeline

- ▶ Piecewise ICP
  - ▶ Diced 15 times, 42.47 sec (first 5 shown)



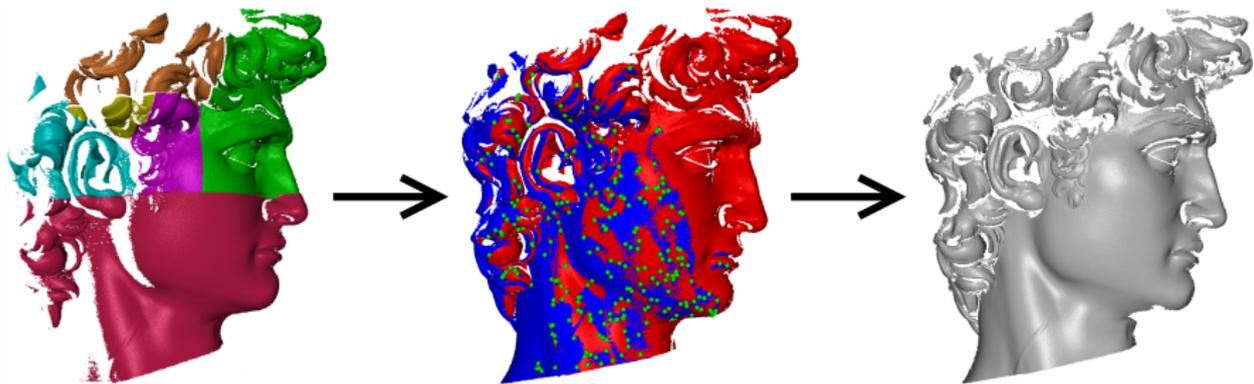
# Pairwise Alignment Pipeline

- ▶ Piecewise ICP
  - ▶ Diced 15 times, 42.47 sec (first 5 shown)
- ▶ TPS Warp
  - ▶ 250 points, .06 sec to compute warp, 6.92 sec to apply it to 323,098 vertices



# Pairwise Alignment Pipeline

- ▶ Piecewise ICP
  - ▶ Diced 15 times, 42.47 sec (first 5 shown)
- ▶ TPS Warp
  - ▶ 250 points, .06 sec to compute warp, 6.92 sec to apply it to 323,098 vertices
- ▶ VRIP volumetric merging step [Curless96]



# Overview

- ▶ Previous Work
  - ▶ Iterative Closest Points (Rigid-Body Alignment)
  - ▶ Hierarchical ICP
- ▶ Non-Rigid Alignment
  - ▶ Thin-Plate Splines
- ▶ Feature Correspondences
  - ▶ Piecewise ICP
- ▶ Pairwise Non-Rigid Alignment
- ▶ Results & Future Work

# Pairwise Alignment Results



right.shoulder.chest.a  
295,012 vertices

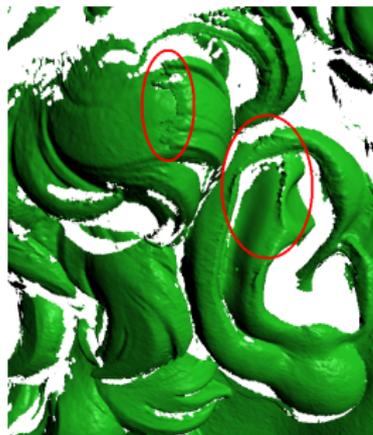


face4.e  
323,098 vertices

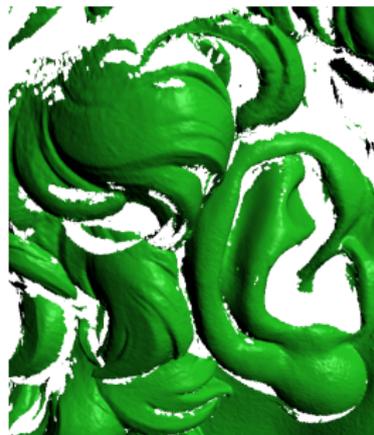


- Alignment Quality
- No overlap
  - Good ICP alignment
  - Good TPS alignment
  - Good ICP & TPS alignments

# Pairwise Alignment Results



ICP Alignment



TPS Alignment



Merged Mesh

# Current Work: Global Alignment Results



16 meshes after global alignment



VRIP merged output

# Future Work and Acknowledgments

- ▶ **Global Registration**
- ▶ Stability and Performance Improvements
  - ▶ Better ICP sampling heuristics
  - ▶ Improve dicing heuristic to reduce number of iterations
- ▶ TPS feature point selection improvements

## Thanks to

- ▶ National Science Foundation
- ▶ Princeton Graphics Group
- ▶ Prof. Ken Steiglitz
- ▶ Natasha Gelfand and Leslie Ikemoto (Hierarchical ICP)

End

# Pairwise Alignment Results



Affine Warp



Full Warp



0 mm

5 mm



Alignment Quality

- No overlap
- Good ICP alignment
- Good TPS alignment
- Good ICP & TPS alignments

# Thin-Plate Splines

- ▶ Thin-plate splines always take the form

**$4 \times n$  non-affine warping parameters ( $WX^t = 0$ )**

$$y = Ax + WK(x)$$

**$4 \times 4$  affine transformation**

**$n \times 1$  control point influence vector**

where  $K(x) = (|x - x_1|, \dots, |x - x_n|)^t$  in 3-D

# Thin-Plate Splines

- ▶ Thin-plate splines always take the form

**$4 \times n$  non-affine warping parameters ( $WX^t = 0$ )**

$$y = Ax + WK(x)$$

**$4 \times 4$  affine transformation**

**$n \times 1$  control point influence vector**

where  $K(x) = (|x - x_1|, \dots, |x - x_n|)^t$  in 3-D

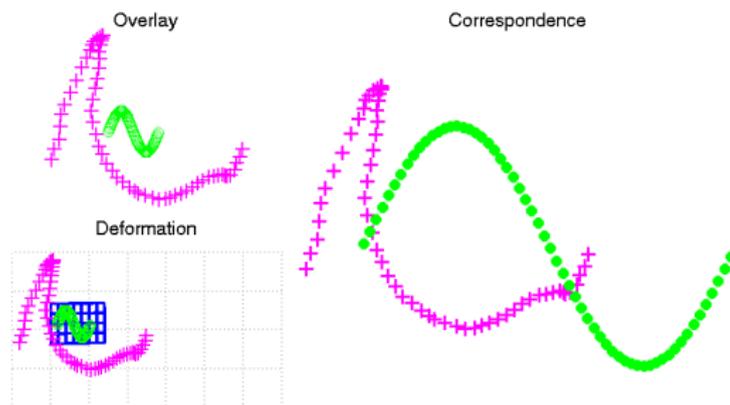
- ▶ The warping coefficients  $A$  and  $W$  are computed by the equation

$$(A \mid W) \left( \begin{array}{c|c} X & 0 \\ \hline K + n\lambda I & X^t \end{array} \right) = (Y \mid 0)$$

where  $K_{ij} = |x_i - x_j|$ .

## Previous Work: Softassign and Deterministic Annealing

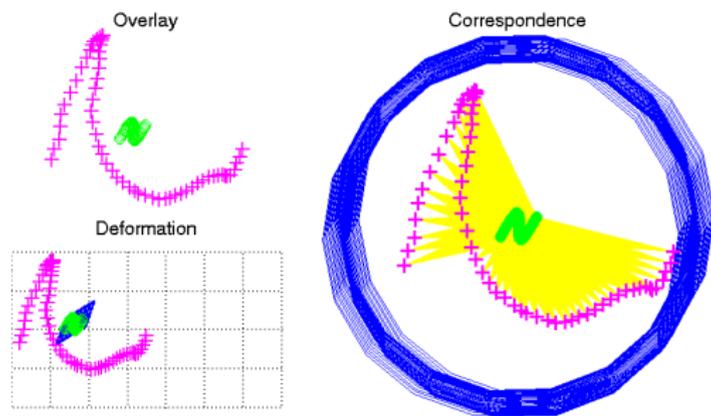
- ▶ Maintain probability that each point in  $X$  maps to each other point in  $Y$  (Softassign)
- ▶ Probability of two points corresponding has Gaussian fall-off with respect to distance
- ▶ Fall-off narrows at each iteration until we reach exact correspondence (Deterministic annealing)



Chui & Rangarajan

## Previous Work: Softassign and Deterministic Annealing

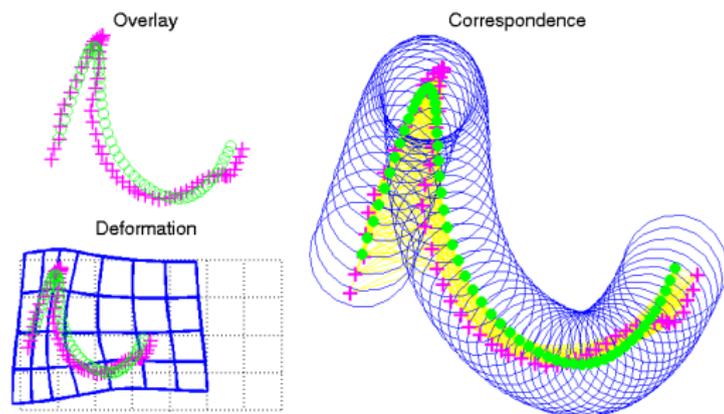
- ▶ Maintain probability that each point in  $X$  maps to each other point in  $Y$  (Softassign)
- ▶ Probability of two points corresponding has Gaussian fall-off with respect to distance
- ▶ Fall-off narrows at each iteration until we reach exact correspondence (Deterministic annealing)



Chui & Rangarajan

## Previous Work: Softassign and Deterministic Annealing

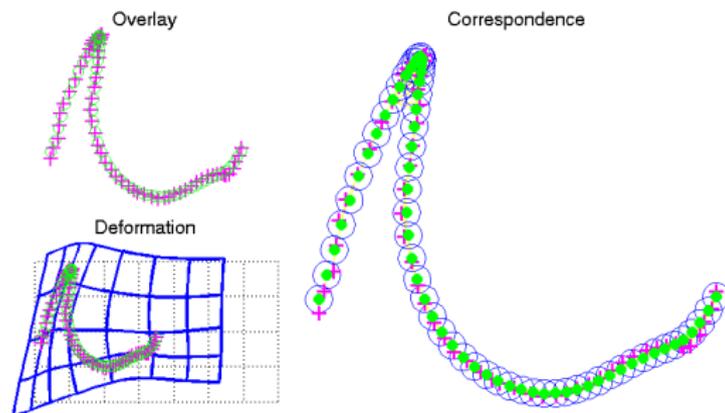
- ▶ Maintain probability that each point in  $X$  maps to each other point in  $Y$  (Softassign)
- ▶ Probability of two points corresponding has Gaussian fall-off with respect to distance
- ▶ Fall-off narrows at each iteration until we reach exact correspondence (Deterministic annealing)



Chui & Rangarajan

## Previous Work: Softassign and Deterministic Annealing

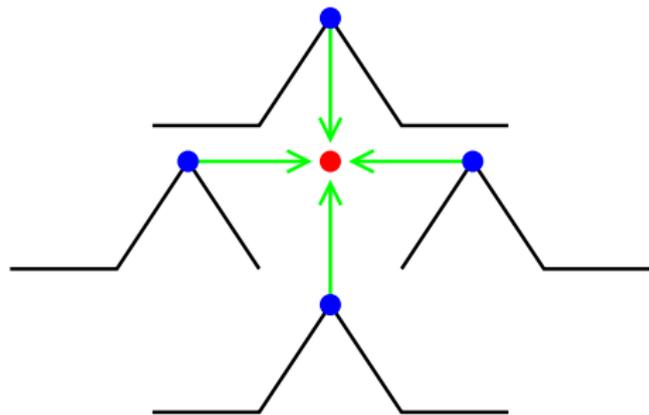
- ▶ Maintain probability that each point in  $X$  maps to each other point in  $Y$  (Softassign)
- ▶ Probability of two points corresponding has Gaussian fall-off with respect to distance
- ▶ Fall-off narrows at each iteration until we reach exact correspondence (Deterministic annealing)



Chui & Rangarajan

# Current Work: Global Alignment

- ▶ Error accumulates over successive alignments
- ▶ Distribute error
  - ▶ across warping function (ICP)
  - ▶ across positions of global feature points in space



# Current Work: Global Alignment

- ▶ Perform best global ICP alignment

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$ 
  - ▶ Randomly select features at constant sampling rate

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$ 
  - ▶ Randomly select features at constant sampling rate
  - ▶ For each overlapping range scan  $S'$

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$ 
  - ▶ Randomly select features at constant sampling rate
  - ▶ For each overlapping range scan  $S'$ 
    - ▶ Align  $S'$  to  $S$  and find feature correspondences

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$ 
  - ▶ Randomly select features at constant sampling rate
  - ▶ For each overlapping range scan  $S'$ 
    - ▶ Align  $S'$  to  $S$  and find feature correspondences
    - ▶ Record position of each feature point on  $S'$

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$ 
  - ▶ Randomly select features at constant sampling rate
  - ▶ For each overlapping range scan  $S'$ 
    - ▶ Align  $S'$  to  $S$  and find feature correspondences
    - ▶ Record position of each feature point on  $S'$
  - ▶ Record mean position of each feature point across all scans on which it falls as its canonical position

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$ 
  - ▶ Randomly select features at constant sampling rate
  - ▶ For each overlapping range scan  $S'$ 
    - ▶ Align  $S'$  to  $S$  and find feature correspondences
    - ▶ Record position of each feature point on  $S'$
  - ▶ Record mean position of each feature point across all scans on which it falls as its canonical position
- ▶ For each range scan  $S$

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$ 
  - ▶ Randomly select features at constant sampling rate
  - ▶ For each overlapping range scan  $S'$ 
    - ▶ Align  $S'$  to  $S$  and find feature correspondences
    - ▶ Record position of each feature point on  $S'$
  - ▶ Record mean position of each feature point across all scans on which it falls as its canonical position
- ▶ For each range scan  $S$ 
  - ▶ Warp all features on  $S$  to their canonical positions

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$ 
  - ▶ Randomly select features at constant sampling rate
  - ▶ For each overlapping range scan  $S'$ 
    - ▶ Align  $S'$  to  $S$  and find feature correspondences
    - ▶ Record position of each feature point on  $S'$
  - ▶ Record mean position of each feature point across all scans on which it falls as its canonical position
- ▶ For each range scan  $S$ 
  - ▶ Warp all features on  $S$  to their canonical positions
- ▶  $O(nm)$  for  $m$  overlapping scans

# Current Work: Global Alignment

- ▶ Perform best global ICP alignment
- ▶ For each range scan  $S$ 
  - ▶ Randomly select features at constant sampling rate
  - ▶ For each overlapping range scan  $S'$ 
    - ▶ Align  $S'$  to  $S$  and find feature correspondences
    - ▶ Record position of each feature point on  $S'$
  - ▶ Record mean position of each feature point across all scans on which it falls as its canonical position
- ▶ For each range scan  $S$ 
  - ▶ Warp all features on  $S$  to their canonical positions
- ▶  $O(nm)$  for  $m$  overlapping scans
- ▶ At most two scans in memory at a time