



3D Non-rigid Registration for MPU Implicit Surfaces

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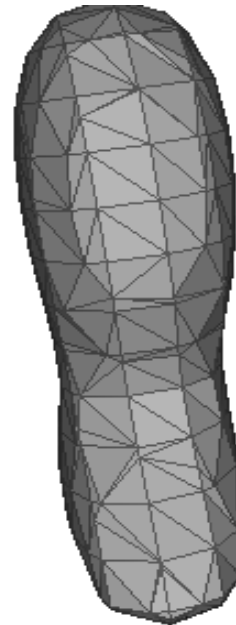


Outline

- Rigid and non-rigid registration
- Implicit Surface and MPU Implicits
- Previous work
- Our proposed method
- Experimental results
- Conclusion and Future work

Rigid registration

- Rigid registration
 - To find the transformation (rotation and translation) between two very similar models or different poses of the same model

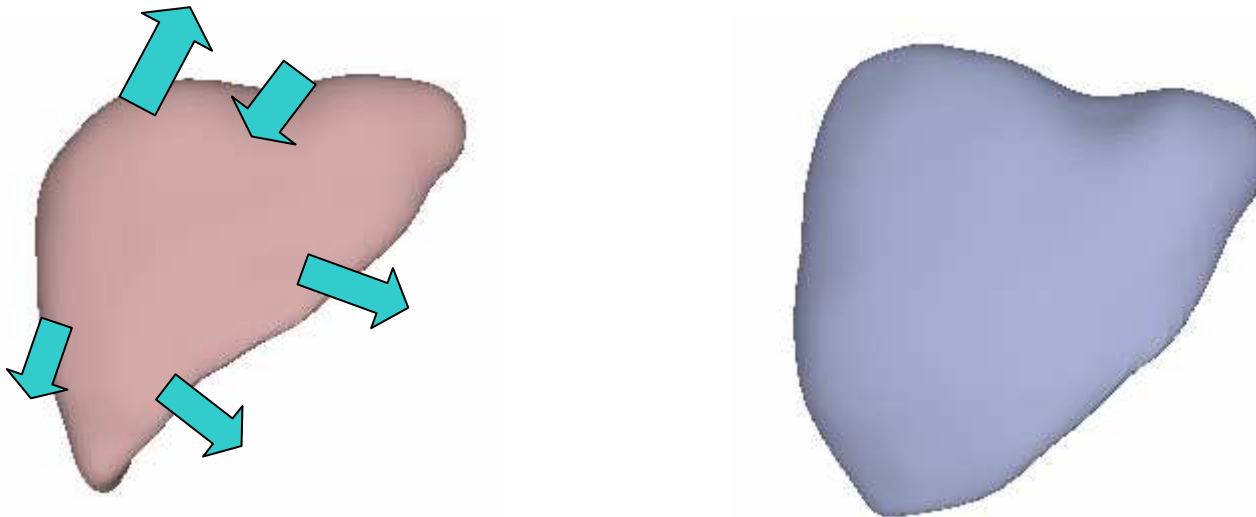


A cartoon bone



Non-rigid registration

- For two models which are deformed versions of the other
 - More degree of freedom is required to represent this deformation.



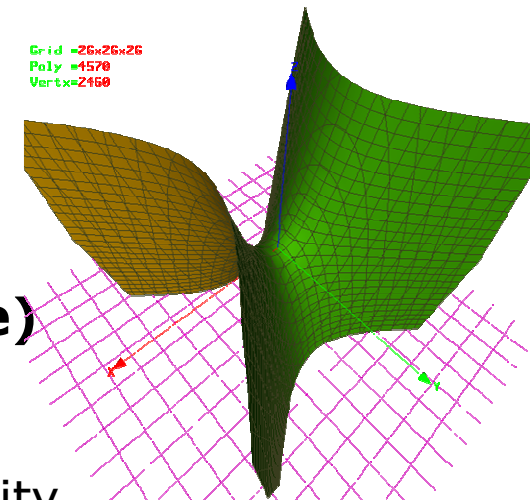
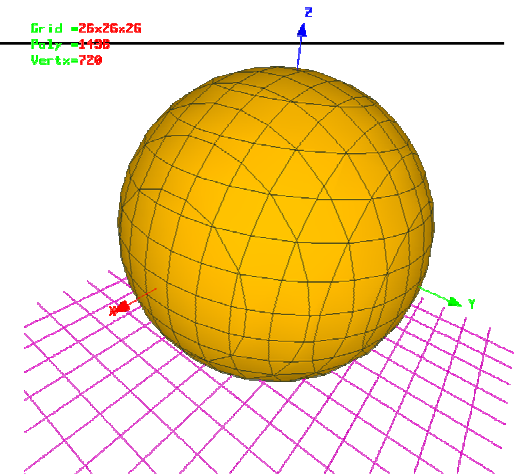


3D Object representation

- Many sources of 3D models
 - Range Scanner
 - Existing object databases
 - Mechanical parts
 - Medical images (volume data)
- Different kinds of object representations
 - Point sets/point clouds
 - Triangular meshes
 - **Implicit surfaces**
 - ...

Implicit Surface

- A function F
 - A surface S can be defined by " $F(x, y, z)=c$ "
- For example,
 - Sphere:
 - $F(x, y, z)=x^2+y^2+z^2-4=0$
 - Hyperbolic paraboloid:
 - $F(x, y, z)=x^2-y^2-z=0$
- Many classes of implicit surfaces
 - metaball surfaces (Blobby)
 - Variational implicit surfaces
 - **Multi-level partition of unity implicits (MPU implicit surface)**



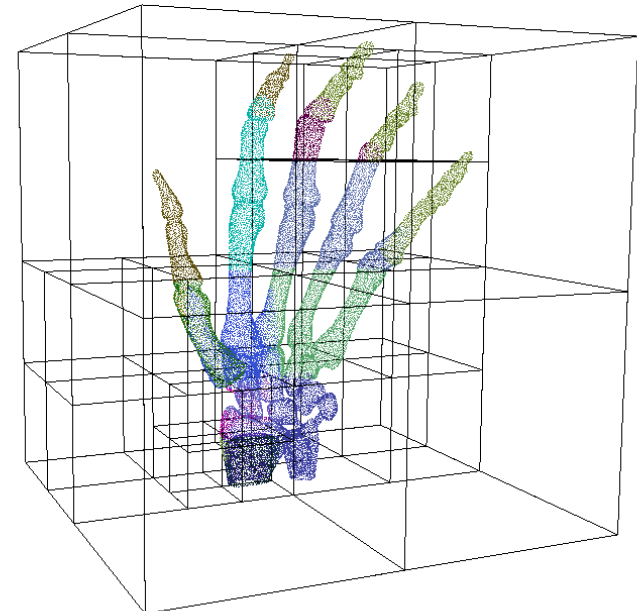
(MPU) Y. Ohtake, et al. Multi-level partition of unity implicits. In SIGGRAPH 2003.

MPU Implicits

- MPU is an error controlled mechanism of creating implicit surfaces. (Ohtake et al.)
 - Octree subdivision
 - Fitting of local shape
 - Smooth blending.

$$f(\mathbf{x}) = \frac{\sum_i \omega_i(\mathbf{x}) f_i(\mathbf{x})}{\sum_i \omega_i(\mathbf{x})}$$

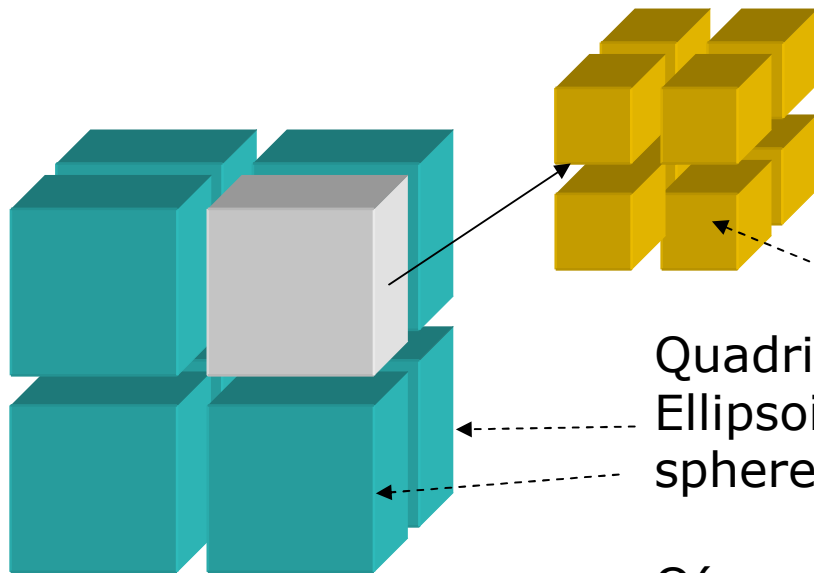
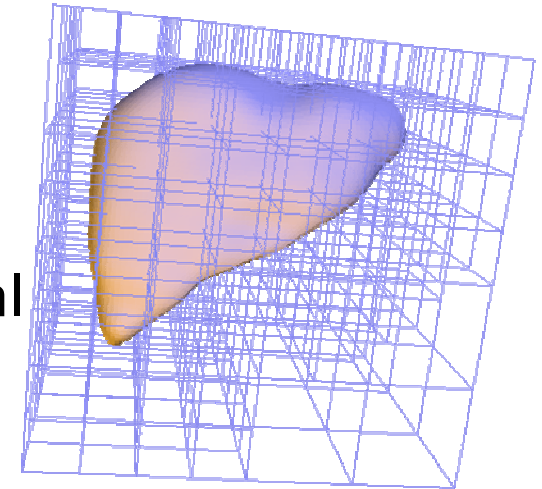
$$Q_j(\mathbf{x}) = 0$$



MPU Implicits

- Local shape function

- **A quadric**
- A quadratic polynomial
- A piecewise quadratic polynomial



Octree

Quadrics in 3D:
Ellipsoid, paraboloid, ...
spheres, cones, cylinders, ...

$$Q(x,y,z) = Ax^2 + By^2 + Cz^2 + Dxy + Eyz + Fxz + Gx + Hy + Iz + J$$



Implicit surfaces and non-rigid registration

- Advantages of IS
 - It can reconstruct surface from range scans and incomplete point data.
 - The functional operations, like offsetting and twisting, can be applied to the implicit function easily.
- Additional advantages of MPU
 - Error-controlled framework
 - The value of the signed distance function at a point can be evaluated rapidly.
 - Some applications: Surface recovery [14], shape completion [15]
- Applications of Registration
 - Reconstructing a complex model from 3D point sets of different views
 - Building a statistical model requires dense correspondence.



Previous work

- Non-rigid registration on two mesh models (Allen et al. [3], Amberg et al. [4])
 - Apply an affine transformation to each point
- Non-rigid registration in implicit spaces (Paragios et al. [5], Huang et al. [6])
 - Sampling points on the space to achieve free-form deformation
 - Cannot be directly applied to implicit surface representation
- Registration and integration of variational implicit surfaces (Claes et al. [7])
 - This method only handles rigid registration

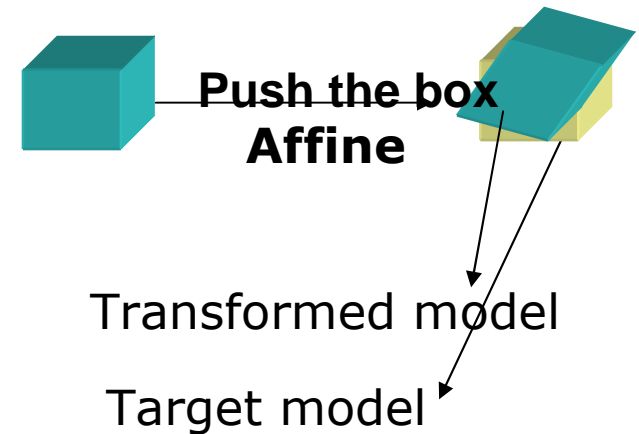
Our proposed approach

Our approach

- Based on MPU framework
- Apply an affine transformation for each box
- Combine affine transformations by partition of unity
- Solve the affine parameters by energy-minimization

Features

- Non-rigid registration between two implicit surface models
- Directly applied to implicit surfaces





Correspondence issue in our approach

- Correspondence between boxes
 - The two models are assumed registered roughly.
 - One cell **C** in source implicit surface corresponds to a cell **corr(C)** in target implicit surface
 - Split the cell in the octree if needed

Blending affine transformations

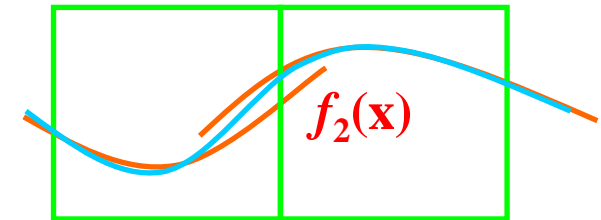
- Continuity of transformed models

- MPU: Blend all implicits f_i with the weighting function w_i

$$f(\mathbf{x}) = \frac{\sum_i w_i(\mathbf{x}) f_i(\mathbf{x})}{\sum_i w_i(\mathbf{x})}$$

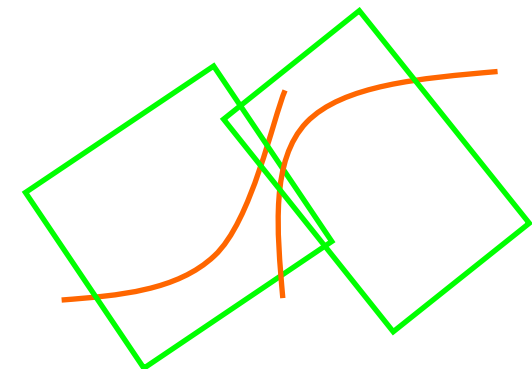
- Our method: Blend all transformed implicits with the corresponding affine p_i

$$doform(\mathbf{x}) = \frac{\sum_i w_i(p_i^{-1}(\mathbf{x})) f_i(p_i^{-1}(\mathbf{x}))}{\sum_i w_i(p_i^{-1}(\mathbf{x}))}$$



$f_1(\mathbf{x})$

$f_2(\mathbf{x})$



$f_1(p_1^{-1}(\mathbf{x}))$

$f_2(p_2^{-1}(\mathbf{x}))$



Energy-Minimization Formulation

- The energy consists of two parts

$$E = \alpha E_{data} + E_s$$

- Data energy
- Smoothness energy

α : constants



Data Energy

Data energy

- The difference of signed distance function
- integration over the range of the cell in the source model

$$E_{data} = \sum_i \int \left\| Q_{corr(i)}^T(p(\mathbf{x})) - Q_i^S(\mathbf{x}) \right\|^2 d\mathbf{x}$$

Quadratics

$$Q(\mathbf{x}) = \mathbf{x}^T \mathbf{A} \mathbf{x} + \mathbf{b}^T \mathbf{x} + c$$

Affine transformation

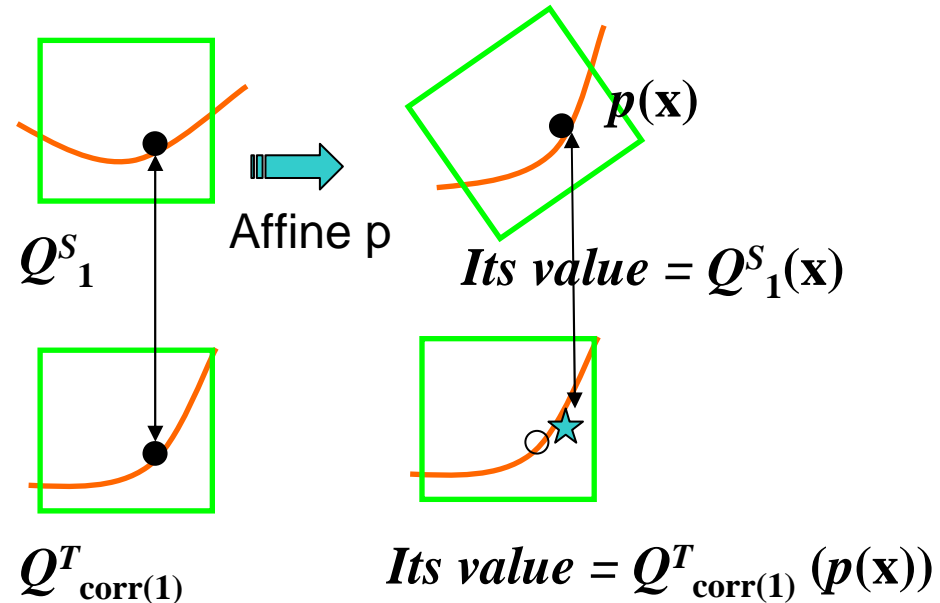
$$p(\mathbf{x}) = \mathbf{K} \mathbf{x} + \mathbf{h}$$

A is a symmetric 3x3 matrix, **b** is a 3x1 matrix, and *c* is a constant
K is a 3x3 matrix and **h** is a 3x1 vector

Data Energy (cont'd)

$$E_{data} = \sum_i \int \left\| Q_{corr(i)}^T(p(\mathbf{x})) - Q_i^S(\mathbf{x}) \right\|^2 d\mathbf{x}$$

- S: source IS
- T: target IS
- corr: correspondence between source and target IS



Point \mathbf{x} in $S \rightarrow$ Point $\mathbf{p}(\mathbf{x})$ in T

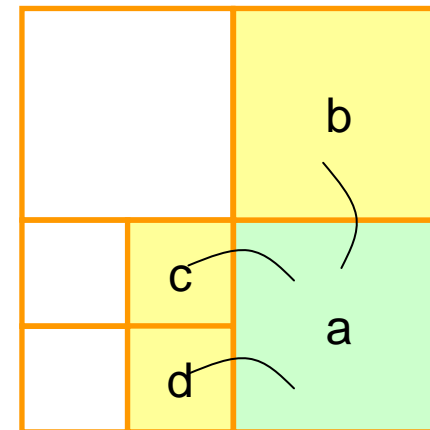
Smoothness energy

- Smoothness energy
 - Make the deformation smooth

$$E_s = \sum_{(i,j) \in AC} \gamma \|\mathbf{K}_i - \mathbf{K}_j\|_F^2 + \delta \|\mathbf{h}_i - \mathbf{h}_j\|_F^2$$

AC is the set of adjacent pairs.
(a, b), (a, c), and (a, d) are in the set AC.

The adjacent cells of a are b, c, and d.





Optimization

- Minimize the energy

$$E = \alpha E_{data} + E_s$$

- Gradient descent method
 - The gradient w.r.t $\{\mathbf{K}_1, \mathbf{h}_1, \mathbf{K}_2, \dots\}$ must be evaluated.
 - The gradient of this energy can be derived in a closed form, because the local shape function is a quadric.



Data energy gradient

$$E = \alpha E_{data} + E_s$$

$$Diff = \left\| Q_{corr(i)}^T (p(\mathbf{x})) - Q_i^S(\mathbf{x}) \right\|^2$$

$$\frac{\partial}{\partial \mathbf{K}_i} E_{data} = \int_{Cell_i} \frac{\partial Diff}{\partial \mathbf{K}_i} d\mathbf{x}$$

$$\frac{\partial Diff}{\partial \mathbf{K}_i} = 2 \left(\frac{\partial Q_{corr(i)}^T}{\partial \mathbf{K}_i} \right) (Q_{corr(i)}^T - Q_i^S(\mathbf{x}))$$

$$\frac{\partial Q_{corr(i)}^T}{\partial \mathbf{K}_i} = \left(2\mathbf{A}_{corr(i)}^T \mathbf{K}_i \mathbf{x} \mathbf{x}^T \right) + \left(\mathbf{A}_{corr(i)}^T \mathbf{h}_i + \mathbf{b}_{corr(i)}^T \right) \mathbf{x}^T$$

A, b: the parameters of quadrics



Smoothness energy gradient

$$\left\{ \begin{array}{l} \frac{\partial}{\partial \mathbf{K}_i} E_s(\gamma, \delta) = \sum_{(i,j) \in AC} 2\gamma(\mathbf{K}_i - \mathbf{K}_j) \\ \frac{\partial}{\partial \mathbf{h}_i} E_s(\gamma, \delta) = \sum_{(i,j) \in AC} 2\delta(\mathbf{h}_i - \mathbf{h}_j) \end{array} \right.$$



Approximation for integration

- The partial derivatives of K_i involve integration over the i th cell.

$$\frac{\partial}{\partial K_i} E_{data} = \int_{Cell_i} \frac{\partial Diff}{\partial \mathbf{K}_i} d\mathbf{x}$$

- We can approximate the integration by discrete method, but we have the formula for the partial derivatives.

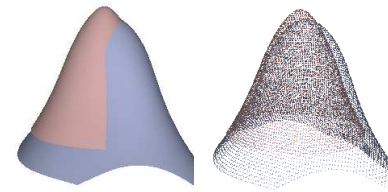
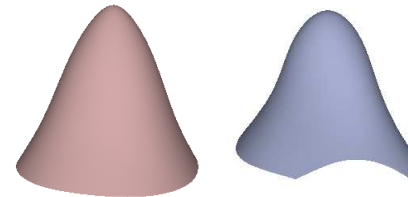
$$\frac{\partial Diff}{\partial \mathbf{K}_i} = 2 \left(\frac{\partial Q_{corr(i)}^T}{\partial \mathbf{K}_i} \right) (Q_{corr(i)}^T - Q_i^S(\mathbf{x}))$$

$$\frac{\partial Q_{corr(i)}^T}{\partial \mathbf{K}_i} = \left(2\mathbf{A}_{corr(i)}^T \mathbf{K}_i \mathbf{x} \mathbf{x}^T \right) + \left(\mathbf{A}_{corr(i)}^T \mathbf{h}_i + \mathbf{b}_{corr(i)}^T \right) \mathbf{x}^T$$

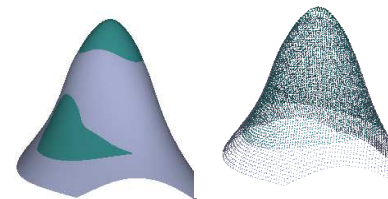
Experimental results (1)

- Geometric objects
 - Open surfaces
- (Initial)
- Before registration
- (Transformed:
green)
- After registration

Source & Target



Average distance error: 0.0895

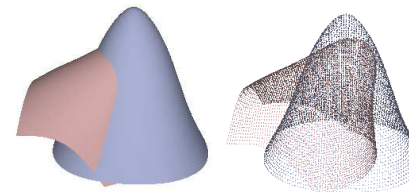
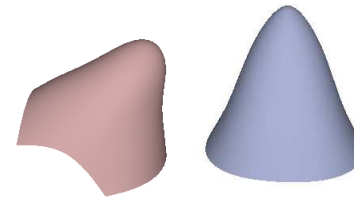


Average distance error: 0.0297

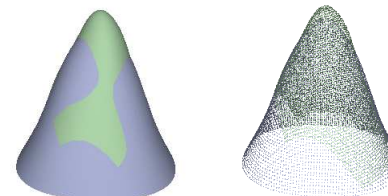
Experimental results (2)

- Geometric objects
 - Open surfaces
- (Initial)
- Before registration
- (Transformed: green)
- After registration

Source & Target



Average distance error: 0.1398



Average distance error: 0.0304

Experimental results (3)

- Geometric objects

- Closed surfaces

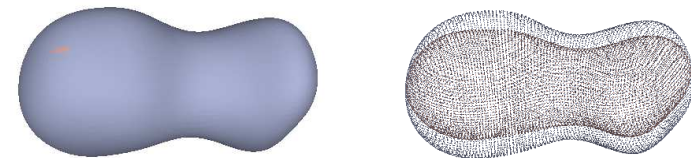
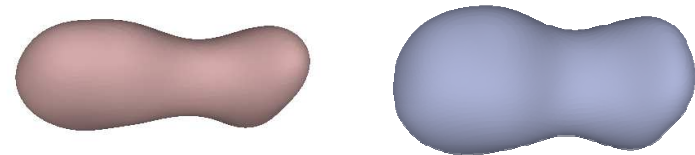
- (Initial)

- Before registration

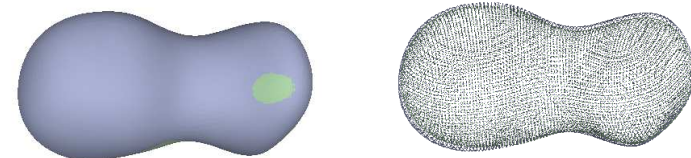
- (Transformed:
green)

- After registration

Source & Target



Average distance error: 0.049

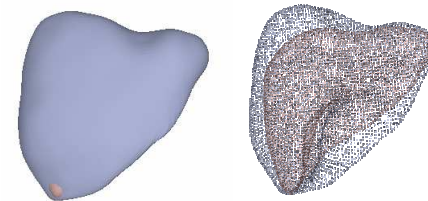
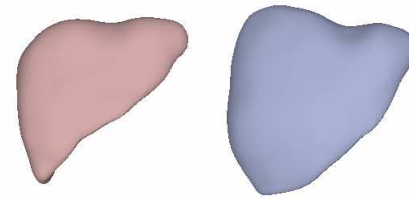


Average distance error: 0.0184

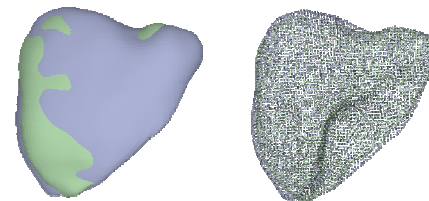
Experimental results (4)

- Human organs
 - Liver
- (Initial)
- Before registration
- (Transformed: green)
- After registration

Source & Target



Average distance error: 7.3192

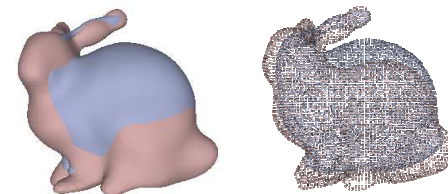
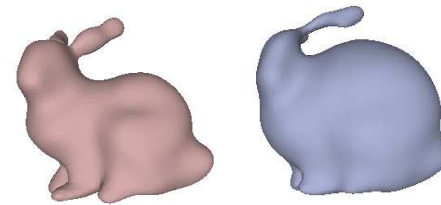


Average distance error: 1.975

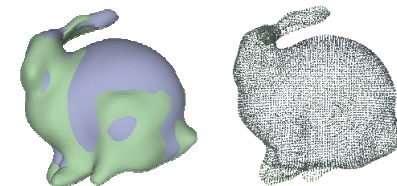
Experimental results (5)

- Sculpture models
 - Bunny
- (Initial)
- Before registration
- (Transformed: green)
- After registration

Source & Target



Average distance error: 0.0769



Average distance error: 0.0279



Conclusion and Future work

- A new 3D non-rigid registration algorithm for implicit surfaces is proposed.
- We do not sample points for registering two implicit surfaces.
- The continuous deformation function is determined by the proposed algorithm in an energy minimization framework.

- In the future, we would like to combine registration and generation of implicit surfaces in a unified framework.



Thank you!