

# Industrial Problem-Solving Workshop on Medical Imaging

# Problem # 2 Rapid Modeling of Internal Structures of Deformable Organs (i.e. Liver)

*Edward Xishi Huang and James Drake* The Hospital for Sick Children



# **Problem definition**

- Accurate estimation of deformation of the soft organ's internal structures between two images acquired at different conditions
- What information are used?!

Point landmarks [1]



Surface information



#### Vessel segments and curves [1]





# Problem definition

- Application: Tumor treatment using high-intensity focused ultrasound (HIFU) thermal procedures.
- Real-time image guidance is required for targeting.
- Intraoperative imaging systems:
  - Low resolution and quality images
  - Long acquisition time
  - Compatibility with other equipments in the operation room.
- Solution: Updating preoperative treatment plans and physical deformation models based on intraoperatively acquired images.
- The idea: Employing boundary conditions (i.e. curves of vessels and bifurcations of vessels, landmarks, and surface information ) to constrain the solution of the deformable model of organ.



# Problem definition

- Registering internal structures and surface information of the two set of images acquired from the soft organ.
- Image Registration

Given a reference image R and a template image T, find a reasonable transformation y, so that the transformed image T[y] is similar to R [2].





Modeling internal structures in 2D images using landmarks and vessel segments with known end points





#### Solution

Landmarks:  $(x_l, x_l)$  and  $(x'_l, y'_l)$  for l = 1, 2, ..., n

Vessel Curves: y = S(x) and y' = S'(x')

Displacement Function: (u(x, y), v(x, y))

Landmarks:  $(x'_l, y'_l) \Leftarrow (x_l + u(x_l, y_l), y_l + v(x_l, y_l))$ 

Any point on the curve:  $(x', y') \Leftarrow (x + u(x, y), y + v(x, y))$ 



#### Solution

The cost function to be minimized for landmarks matching:

$$J_1(u,v) = \sum_{l=1}^n \left\{ \left( x_l' - x_l - u(x_l, y_l) \right)^2 + \left( y_l' - y_l - v(x_l, y_l) \right)^2 \right\}$$

The cost function to be minimized for curve matching:

$$(x, S(x)) \Rightarrow (x+u(x, S(x)), S(x)+v(x, S(x)))$$
  
This point corresponds to

$$(x, S(x)) \implies (x + u(x, S(x)) , S'(x + u(x, S(x))))$$
  
$$J_2(u, v) = \int_{x_1}^{x_2} |S'(x + u(x, S(x))) - S(x) - v(x, S(x))|^2 dx$$

# **FIELDS**

# Problem 1

### Solution

The total cost function to be minimized for landmarks and curve matching:

$$J(u, v) = w_1 J_1(u, v) + w_2 J_2(u, v)$$

Having the variational model in optimization model form:

$$u = Ax + By + x_0 + \sum_{i=1}^{N} a_i \varphi_i(x, y)$$
$$v = Cx + Dy + y_0 + \sum_{i=1}^{N} b_i \varphi_i(x, y)$$

 $\varphi_i$  (*i* = 1, 2, ..., *N*) are radial basis functions.

The cost function in terms of unknown parameters

min 
$$J(A, B, C, D, x_0, y_0, a_1, ..., a_N, b_1, ..., b_N)$$



Modeling internal structures in 2D images using landmarks and vessel segments with one end point.





### Solution

 $(x_e, y_e)$  is unknown point to be found and needs to be added to the optimization function as follows:

$$J_{2}(x_{e}, u, v) = \left(x_{e}' - x_{e} - u\left(x_{e}, S(x_{e})\right)\right)^{2} + \left(y_{e}' - y_{e} - v\left(x_{e}, S(x_{e})\right)\right)^{2} + \int_{x_{1}}^{x_{e}} \left|S'\left(x + u\left(x, S(x)\right)\right) - S(x) - v\left(x, S(x)\right)\right|^{2} dx$$



### Modeling internal structures in 3D image

Landmarks: The same as 2D images

 $J_{1}(u, v, w) = \sum_{l=1}^{n} \left\{ \left( x_{l}' - x_{l} - u(x_{l}, y_{l}, z_{l}) \right)^{2} + \left( y_{l}' - y_{l} - v(x_{l}, y_{l}, z_{l})^{2} + \left( z_{l}' - z_{l} - v(x_{l}, y_{l}, z_{l})^{2} \right)^{2} \right\}$ 

#### > Curves:

Parametric cubic representation: piecewise spline

$$x(t) = a_{x}t^{3} + b_{x}t^{2} + c_{x}t + d_{x}$$
$$y(t) = a_{y}t^{3} + b_{y}t^{2} + c_{y}t + d_{y}$$
$$z(t) = a_{z}t^{3} + b_{z}t^{2} + c_{z}t + d_{z}$$



Registration based on surface matching of the object in two set of images





#### **\*** The cost function to be minimized:



J(u,v,w) =

 $\int_{\Omega} \left| S'\left( x + u\left( x, y, S(x, y) \right), y + v\left( x, y, S(x, y) \right) \right) - S(x, y) - w\left( x, y, S(x, y) \right) \right|^2 dx \, dy$ 

Another solution: deformable surface modeling using active contours [3]



### Impact

- **\*** FEM-based image registration.
- Intensity based [4]

$$\min J(u) = D(T[u], R) + \alpha \frac{1}{2}u^{T}Ku; \quad \alpha \in \Re_{+}$$
$$\frac{\partial J(u)}{\partial u} = \frac{\partial D(T[u], R)}{\partial u} + \alpha Ku = 0$$
$$Ku = f(u) = -\frac{1}{\alpha} \frac{\partial D(T[u], R)}{\partial u}$$

- Multimodality
- Local minima



### Impact

### FEM-based image registration.

### Feature based

Internal structures and surface information of the deformable organ provides necessary boundary condition to solve the FEM-based deformation equation.

*Example:* Linear finite element model of the brain shift and deformation [3].





Impact

#### **\*** FEM-based image registration.







# References

- [1] Dietlind Zühlke, Sven Arnold, Gernoth Grunst, Peter Wißkirchen, "Intrainterventional registration of 3D ultrasound to models of the vascular system of the liver" GMS CURAC 2007, Vol. 2(1)
- [2] J. Modersitzki, Numerical Methods for Image Registration. New York:Oxford, 2004.
- [3] M. Ferrant, A. Nabavi, B. Macq, F. Jolesz, R. Kikinis, and S. Warfield, "Registration of 3D Intraoperative MR Images of the Brain Using a Finite-Element Biomechanical Model," IEEE Trans. on Medical Imaging, vol. 20, no. 12, pp. 1384–1397, 2001.
- [4] B. Marami, S. Sirouspour, and D. Capson, "Model-Based Deformable Registration of Preoperative 3D to Intraoperative Low-Resolution 3D and 2D Sequences of MR Images," in MICCAI 2011, pp. 460–467, 2011.



### **Group Members**

Edward Xishi Huang C. Sean Bohun Tian Chen Jamil Jabbour Ken Jackson Iain Moyles Cartihk Sharma Yongji Tan Bahram Marami

#### Motivation

- Modelling a three-dimensional image of the liver is computationally expensive (and has challenging physics)
- Image data arrives in several two-dimensional cross sections (slices) as the body is scanned
- Each slice is identified by unique markers (landmarks and curves)

• If all of the markers from one slice map to all be on a transformed slice then we can consider a series of two-dimensional transformations

#### Setup

- Landmarks
  - The N distinguishing points on image
- Curves
  - The  $\kappa$  distinguishing curves (vessels) on image
- Assume a transformation from "pre-image" (X, Y) to "post-image"  $(\tilde{X}, \tilde{Y})$  via a transformation  $(\bar{X}, \bar{Y})$

$$ar{X} = X + \sum_{j} a_{j} \phi_{j}(X, Y),$$
  
 $ar{Y} = Y + \sum_{j} b_{j} \phi_{j}(X, Y),$ 

•  $\phi_j$  are radial basis functions (RBF)

$$\phi_j(X, Y) = \exp\left(-\frac{(X - X_j)^2 + (Y - Y_j)^2}{\sigma}\right)$$

•  $(X_j, Y_j)$  are the *L* allocation points to form a basis set  $(L \leq N)$ 

#### Setup

- For curves we assume there exists a mapping for curve points on the pre-image (xx, yy) given by yy = S(xx)
- Similarly there exists a map  $\tilde{yy} = \tilde{S}(\tilde{xx})$  for the curve points on the post-image  $(\tilde{xx}, \tilde{yy})$
- Often the form of S and  $\tilde{S}$  will be through an interpolation (cubic splines)

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• The curves have the requirement that the endpoints are landmarks

#### Pre Image



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#### Post Image



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#### Optimization

- We wish to determine the coefficients for the RBF that transforms the pre-image into the post-image
- We determine these by minimizing an error function composed of matching landmarks and curves
- Therefore we consider
  - Landmark Error
    - We wish all terms of the form  $\tilde{X}-\bar{X}$  to be small so that the landmarks are close
  - 2 Curve Error
    - We wish the curve points to be close as well i.e.  $\vec{xx} \vec{xx}$  and  $\tilde{S}(\vec{xx}) \bar{S}(xx)$  are small

• The predicted curve  $\bar{S}(xx) = S(xx) + \sum_j b_j \phi_j(xx, S(xx))$ 

#### Solution



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#### Constrained Optimization

- There are many local minima to this problem with large energies
- In fact, there are many local minima with small energies that don't represent the "true" solution (lack of global minimizer?)
- Idea: Build in a constraint for each curve that forces the area under the post-image curve to match that of the predicted curve

$$\int_{\tilde{x}_{x_1}}^{x_{x_2}} (\tilde{S}(\tilde{x}) - S(xx) - \sum_j b_j \phi_j) \, \mathrm{d}\tilde{x} = 0$$

#### Solution



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#### Conclusions

- Created image data
- Performed an optimization to recover RBF coefficients that transform pre-image to post-image

• Included integral constraints to reduce set of minimizers

#### **Future Work**

- Apply to real landmark data
- Consider weightings carefully
  - Center of mass type penalty system
  - Voronoi diagrams
- Allow for curve endpoints to move