# Image Analysis for Volumetric Industrial Inspection and Interaction

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- (CT) reconstruction from few projections
- Interpolation of low resolution images
- The Virtual Knife interacting with 3D volumes with fast visual feedback

# Motivation - Industrial application of CT

- Fast, inexpensive scanning using a minimum of projections
- Scanning pig backs
  - Quality assesment (lean meat, fat %)
  - Robot control rind trimming
  - Visualization product development

## **Ray Attenuation Model**

- Discretise line integral of attenuation coefficients
- The measured attenuation b<sub>j</sub> is a weighted sum of pixels traversed by the ray
- Pixel weights length of ray's path through it  $b_i = a_1 x_{(1,2)} + a_2 x_{(1,3)} + a_3 x_{(2,3)} + a_4 x_{(2,4)} + a_5 x_{(3,4)}$

Resulting linear system

 $\mathbf{b} = \mathbf{A}\mathbf{x}$ 



#### Fan beam - Image Acquisition

- 100 fan-beam projections of 360 rays each
- Measured on arc-shaped detector array opposite source





### **Filtered Back Projection**

- Does well with *full angle data* 
  - 360x360 image from
    - 360 source positions with 909 rays each









#### **Filtered Back Projection**

- Not so good with *sparse data* 
  - fewer source positions
  - **30** source positions, 909 rays each







## **Reformulate – Probabilistic Approach**

Bayes' theorem

$$p(\mathbf{x}/\mathbf{b}) \propto p(\mathbf{x}) p(\mathbf{b}/\mathbf{x})$$

The loglikelihood of the data

$$\log p(\mathbf{b} | \mathbf{x}) = \left\| \mathbf{b} - \mathbf{A} \mathbf{x} \right\|^2 / 2\sigma^2 + c$$

- Pig CTs are piece-wise constant prior should
  - penalise intensity roughness
  - allow for *jumps* on edges





# **Prior Formulation**

• Penalise large gradients - finite difference operators: L<sub>1</sub>x, L<sub>2</sub>x

$$\log p(\mathbf{x}) = -\frac{1}{2} \left( \left\| \mathbf{L}_1 \mathbf{x} \right\|^2 + \left\| \mathbf{L}_2 \mathbf{x} \right\|^2 \right) + c = -\frac{1}{2} \mathbf{x}^T \left( \mathbf{L}_1^T \mathbf{L}_1 + \mathbf{L}_2^T \mathbf{L}_2 \right) \mathbf{x} + c$$

• But only at a sparse set of edge points

$$\log p(\mathbf{x}|\boldsymbol{\theta})p(\boldsymbol{\theta}) = -\frac{1}{2}\mathbf{x}^{T}(\mathbf{L}_{1}^{T}\mathbf{D}^{-1}\mathbf{L}_{1} + \mathbf{L}_{2}^{T}\mathbf{D}^{-1}\mathbf{L}_{2})\mathbf{x} + \log p(\boldsymbol{\theta}) + c$$

$$\mathbf{D} = \operatorname{diag}(\theta_1, \cdots, \theta_N)$$

$$\theta_{j} \sim \Gamma(\alpha, \theta_{0})$$

# Reconstruction

- Choose  $(x, \theta)$  to maximise the posterior probability
- Conjugated Gradient Least Squares
- Two-step algorithm.
  - Fix  $\theta$ , minimise wrt. X
  - Fix x, minimise wrt. Θ
- Works also for cone beam CT.

#### ... Now some images!

- Only few two-step-sweeps needed...
- 360x360 image from 100 fans of 540 rays
- The prior acts as wanted







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• 50 fans of 540 rays







• 40 fans of 540 rays







• 30 fans of 540 rays







#### • 20 fans of 540 rays (pushing it)





• 10 fans of 540 rays (*really* pushing it)





# **Motivation - Interpolation**

- In-plane resolution higher than through plane
- Also to compensate for motion



Through-plane: 8mm slice thickness + 1mm gap



In-plane: 1mm



#### Interpolation

• Linear interpolation: Weighted average of neighboring voxels





z-axis

Original

Linear



#### Improved correspondence-based interpolation

- Adjacent slices:  $I_A$ ,  $I_B$
- Register  $I_A$  to  $I_B$  and vice versa, obtain displacements  $w_{AB}$ ,  $w_{BA}$
- z-position of desired interpolated value, / gives the distance ratio,  $\alpha = (z_I - z_B)/(z_A - z_B)$
- Determine intensities at  $z_I$  between  $I_A$  and  $I_B$ :

$$\mathbf{I} = (1 - \alpha) \mathbf{I}_{\mathbf{A}}(\varphi_{\mathbf{B}\mathbf{A}}(\mathbf{X}, \alpha \mathbf{w}_{\mathbf{B}\mathbf{A}})) + \alpha \mathbf{I}_{\mathbf{B}}(\varphi_{\mathbf{A}\mathbf{B}}(\mathbf{X}, (1 - \alpha)\mathbf{w}_{\mathbf{A}\mathbf{B}}))$$

Penney et al . Registration-based Interpolation, IEEE-TMI 2004 Frakes et al. A New method for Registration-based Interpolation, IEEE-TMI 2008 Olafdottir et al. Improving Image Registration using Correspondence Interpolation, ISBI 2011

### Formulation with respect to Linear Interpolation

Improved Correspondence-based interpolation

 $\mathbf{I} = (1 - \alpha)\mathbf{I}_{\mathbf{A}}(\varphi(\mathbf{X}, \alpha \mathbf{w}_{\mathbf{B}\mathbf{A}})) + \alpha \mathbf{I}_{\mathbf{B}}(\varphi(\mathbf{X}, (1 - \alpha)\mathbf{w}_{\mathbf{A}\mathbf{B}}))$ 

Linear Interpolation



Approximation: Assuming smoothness and dense correspondence field

### **Cardiac example**



Original



Correspondence-based interp



Original



z-gradient with linear interpolation



Correspondence-based





z-gradient with correspondence-based

# Gradients of deformed targets, $\frac{\partial \mathbf{T}}{\partial \varphi}$

#### cardiac MRI



Linear



Spline



Correspondence



# Atlas Building





Linear

Correspondence



#### Interaction – Phantom Omni







# Interaction by proxy

• Plane estimation on surface

Constant re-evaluation

Real-time Performance





# **Linear Interpolation**







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# **Motion compensation**

Phantom



Low resolution





Comp. stack 1 •



Motion stack 1
Motion stack 2



• Comp. stack 2





# Conclusion

- We have demonstrated that
- Iterative reconstruction using smart priors allows for
- Image reconstruction using fewer projections at low resolution, and

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• Motion compensation

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