## Gradient-Based Differential Approach for Patient Motion Compensation in 2D/3D Overlay

**3D** 2014

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Jian Wang 12/10/2014

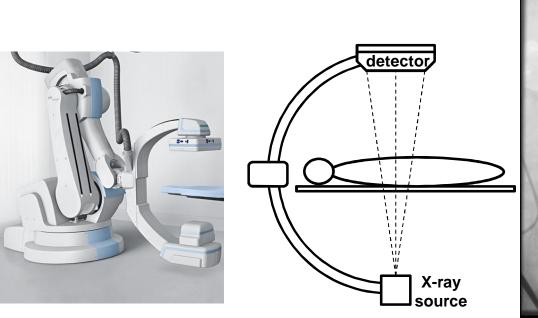
International Conference on 3D Vision The University of Tokyo, Tokyo, Japan December 8th - 11th, 2014



## Vascular & interventional radiology



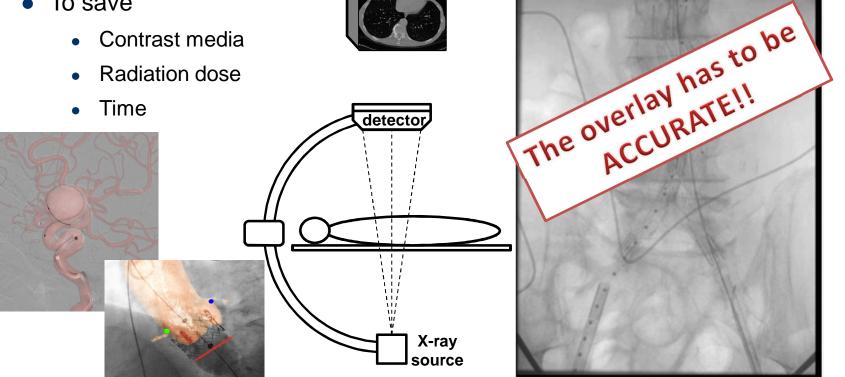
- Interventional C-arm system
  - Fluoroscopy: real-time guidance
  - Interventional devices
  - Vascular structure (contrast media)





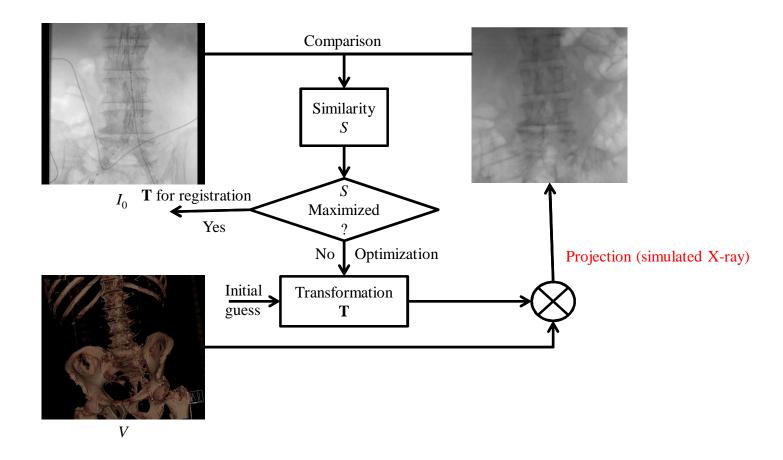
#### $\sim$ 2D/3D overlay during the intervention **SIEMENS**

- 3D image (CT/MR ...) onto 2D fluoroscopy
  - Structures not visible in X-ray images
  - Planning information
- To save
  - Contrast media

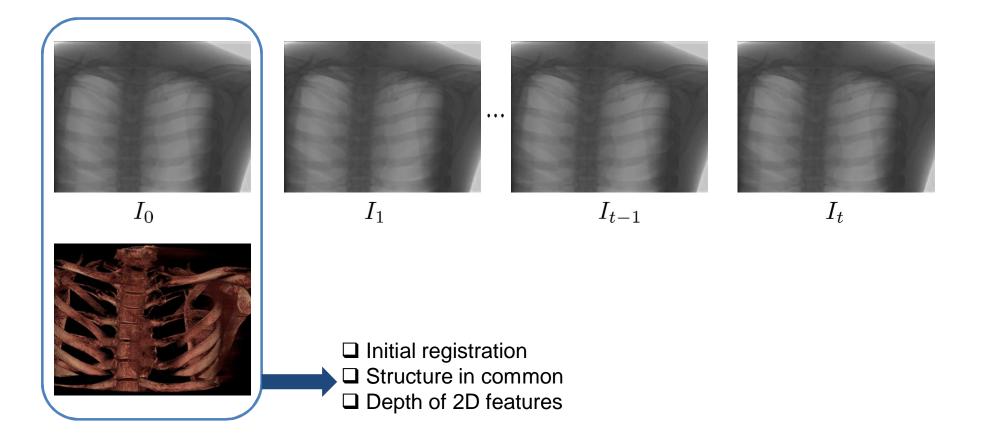


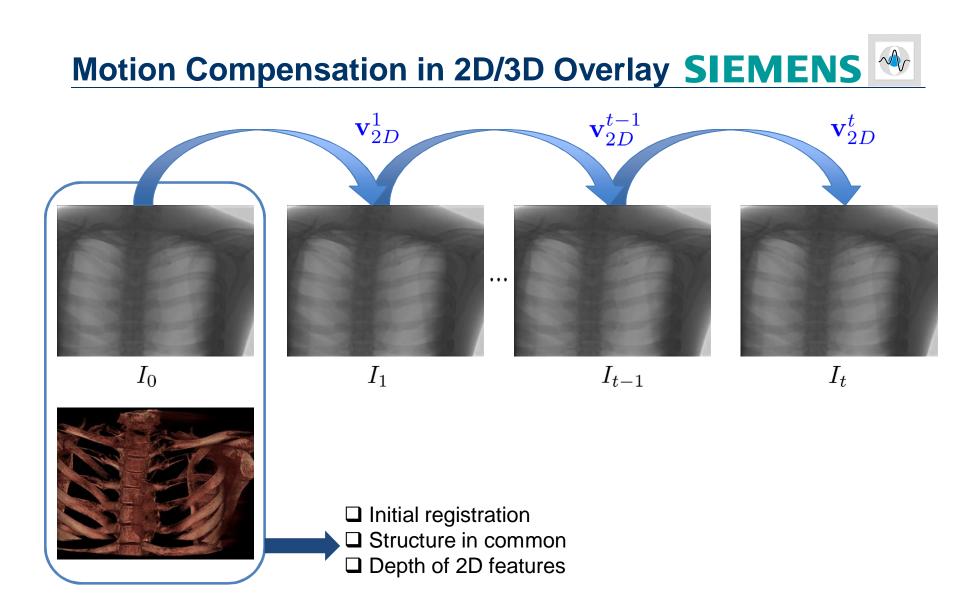


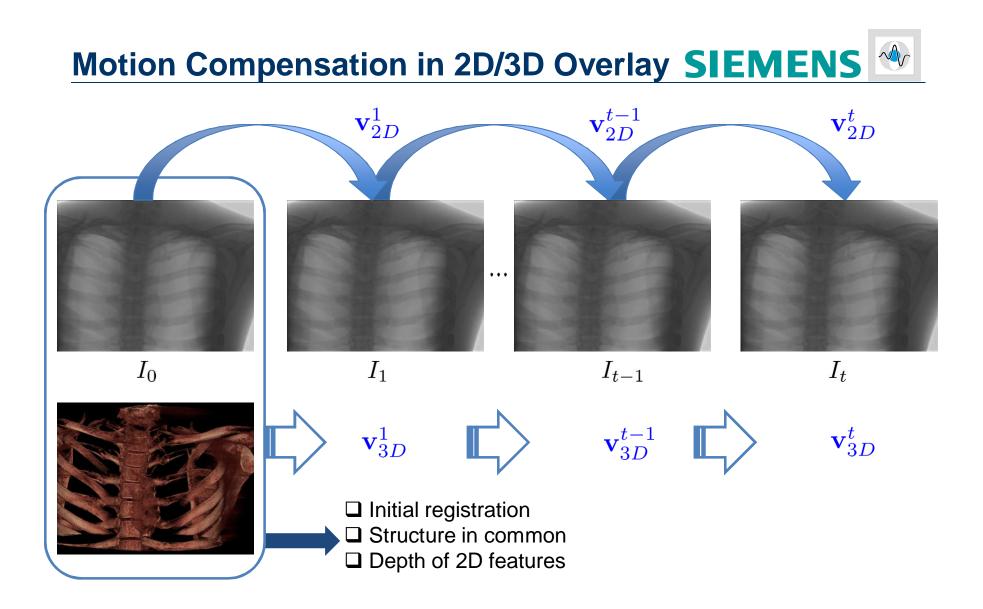
- Iterative optimization based on digitally reconstructed radiograph (DRR)
  - Usually **not real-time capable** for motion correction



# Motion Compensation in 2D/3D Overlay SIEMENS





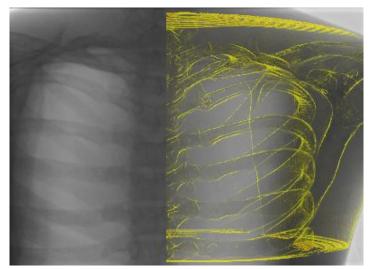


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## Gradient-Based Differential Approach SIEMENS

- Small motion assumption
  - Differential form of 3D rigid motion, i.e. rotation and translation
- Observed motion vs. image gradient
  - Motion observed along gradient direction (2D and 3D)
- Contours / edges are important for motion estimation
  - 2D: border of a region with remarkably different attenuation values
  - 3D: gradient perpendicular with viewing direction





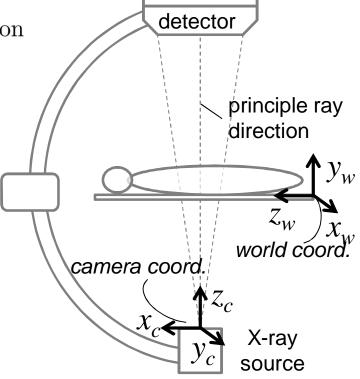
## The Projection Model of C-Arm System SIEMENS

• Pinhole camera model

 $\mathbf{x} \doteq \mathbf{P}\mathbf{w}$ , where  $\mathbf{w}$  is 3D point and  $\mathbf{x}$  is 2D projection

• The projection matrix in camera coordinate system

$$\mathbf{P}_e = \mathbf{K} \left[ \mathbf{I} | \mathbf{0} 
ight] \in \mathbb{R}^{3 imes 4}$$



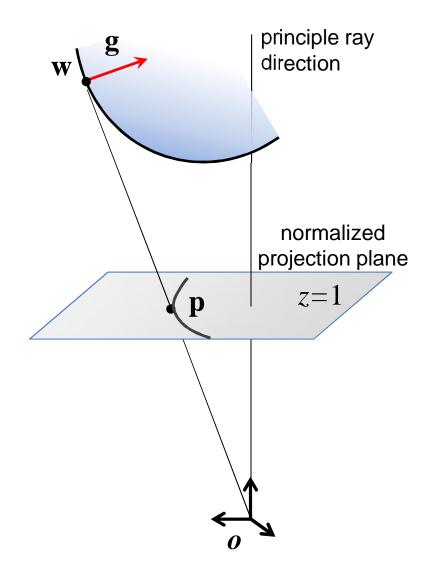
### **The Geometric Setup**



- Normalized back-projection
  - 2D projection point  $\mathbf{x} = (u, v)$
  - The normalized back-projection **p**

$$\mathbf{p} = \left| \mathbf{K}^{-1} \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} \right|_{H}$$

$$\left| \begin{pmatrix} x \\ y \\ w \end{pmatrix} \right|_{H} = \begin{pmatrix} x/w \\ y/w \\ 1 \\ 1 \end{pmatrix}$$



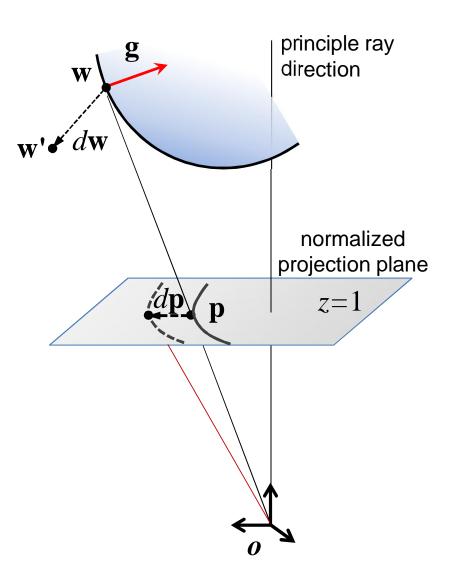
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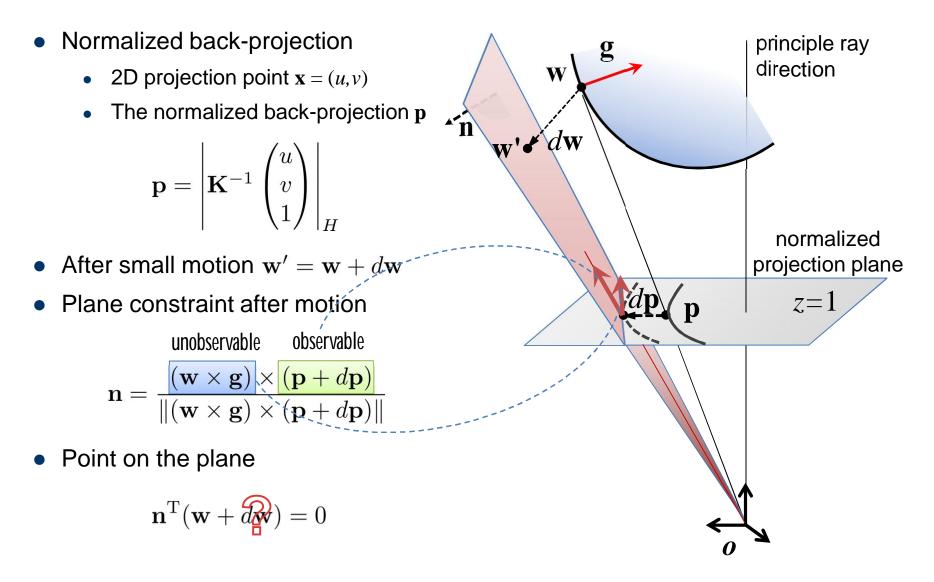
$$\mathbf{p} = \left| \mathbf{K}^{-1} \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} \right|_{H}$$

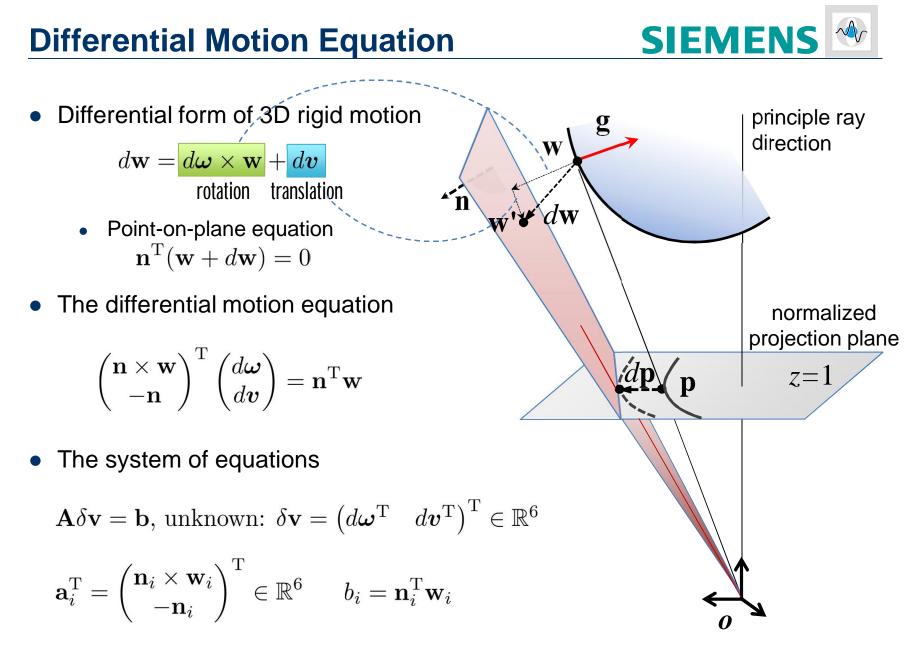
• After small motion  $\mathbf{w}' = \mathbf{w} + d\mathbf{w}$ 



### **The Geometric Setup**







#### 3D volume analysis & 3D selection

- Intensity windowing
- gradient thresholding
- Occluding contour points selection
  - 2D: gradient magnitude
  - 2D/3D: patch-wise similarity
  - 3D:View-gradient perpendicularity

$$\alpha = \arccos\left(\left|\frac{\mathbf{g} \cdot \mathbf{w}}{\|\mathbf{g}\| \cdot \|\mathbf{w}\|}\right|\right)$$

 $\{\mathbf{w}_i, \mathbf{g}_i, \mathbf{p}_i\}_{\text{sel}}$ 

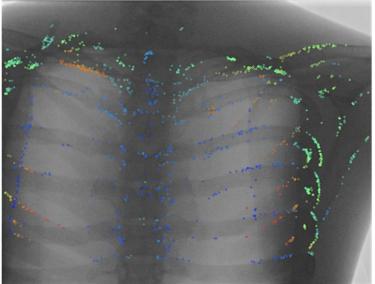
• Selection:

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## **Occluding Contour Point Selection**

- Volume pre-processing
  - 3D guided image filter







## **Tracking and Motion Estimation**



- 2D tracking (*d***p**)
  - Kanade-Lucas-Tomasi optical flow
- Iteratively re-weighted least squares (IRLS)

Reminder of the linear equation  

$$\begin{pmatrix} \mathbf{n} \times \mathbf{w} \\ -\mathbf{n} \end{pmatrix}^{\mathrm{T}} \begin{pmatrix} d\boldsymbol{\omega} \\ d\boldsymbol{v} \end{pmatrix} = \mathbf{n}^{\mathrm{T}} \mathbf{w}$$

$$\mathbf{n} = \frac{(\mathbf{w} \times \mathbf{g}) \times (\mathbf{p} + d\mathbf{p})}{\|(\mathbf{w} \times \mathbf{g}) \times (\mathbf{p} + d\mathbf{p})\|}$$

$$\mathbf{A}\delta\mathbf{v} = \mathbf{b} \Rightarrow \widehat{\delta\mathbf{v}} = \arg\min_{\delta\mathbf{v}} \sum_{i}^{N} \beta_i \left(\mathbf{a}_i^{\mathrm{T}}\delta\mathbf{v} - b_i\right) \text{, where } \beta_i = \beta_{z,i} \cdot \beta_{r,i}$$

- The observation weight  $\beta_{z,i}$ 
  - Tracking error term and the view-gradient perpendicularity
- The residual weight

$$\beta_{r,i}^{(t)} \sim 1/r(\delta \mathbf{v}^{(t-1)})$$

• The residual term at *t*-th iteration is

$$r(\delta \mathbf{v}^{(t-1)}) = \mathbf{a}_i^{\mathrm{T}} \widehat{\delta \mathbf{v}}^{(t-1)} - b_i$$

## **Experiment: Data Acquisition**



- Image acquisition
  - Interventional C-arm system
  - 3D C-arm CT volume
  - 2D fluoroscopic sequences
  - Motion triggered manually

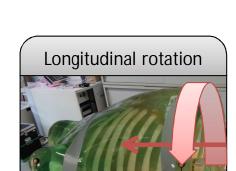
- Ground-truth motion acquisition
  - OptoTrak motion capture system



### **3D Motion Error Statics**

- The **motion recovery rate** for motion component *m*  $r(m) = 1 - \epsilon(m) / \max|m^*|$
- Major motion recovery
  - In-plane:  $r(R_y) = 97.4\%$ ,  $r(t_x) = 95.4\%$ ,  $r(t_z) = 96.7\%$
  - Off-plane rotation:  $r(R_z) = 79.9\%$

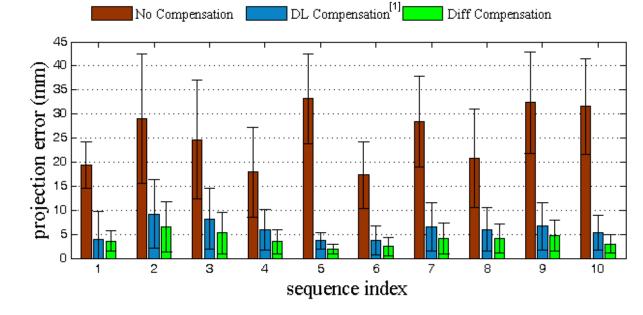
	seq.	# fr.	$\max  R_x^* (^\circ)$	$\epsilon(R_x)(^\circ)$	$\max  R_y^* (^\circ)$	$\epsilon(R_y)(^\circ)$	$\max  R_z^* (^\circ)$	$\epsilon(R_z)(^\circ)$
	1	33	0.18	$0.04 \pm 0.02$	0.97	$0.05\pm0.03$	4.48	$0.93\pm0.43$
	2	93	0.80	$0.43 \pm 0.26$	0.52	$0.05\pm0.03$	11.93	$2.82 \pm 1.55$
	3	111	0.63	$0.40 \pm 0.18$	0.38	$0.01\pm0.01$	10.7	$2.59 \pm 1.04$
	4	111	0.27	$0.12\pm0.11$	0.56	$0.03\pm0.02$	8.31	$1.51\pm0.94$
	5*	110	0.06	$0.07 \pm 0.03$	10.0	$0.37\pm0.16$	0.04	$0.18\pm0.08$
	7	105	0.23	$0.36 \pm 0.26$	4.43	$0.08\pm0.07$	6.82	$1.54\pm0.90$
	8	117	0.26	$0.32\pm0.18$	1.47	$0.04\pm0.03$	7.93	$1.32\pm0.83$
	9	114	0.18	$0.10\pm0.06$	4.57	$0.15\pm0.08$	8.13	$1.89 \pm 0.92$
3	seq.	# fr.	$\max  t_x^*  (\mathrm{mm})$	$\epsilon(t_x)(\mathrm{mm})$	$\max  t_y^* (mm)$	$\epsilon(t_y)(\mathrm{mm})$	$\max  t_z^*  (\mathrm{mm})$	$\epsilon(t_z)(\mathrm{mm})$
0	1	33	2.76	$1.13\pm0.67$	0.99	$2.27 \pm 1.66$	0.16	$0.09\pm0.07$
	2	93	4.58	$2.96 \pm 1.63$	0.71	$2.06 \pm 1.01$	0.61	$0.64 \pm 0.39$
	3	111	4.19	$3.11 \pm 1.32$	0.66	$3.41 \pm 1.37$	0.65	$0.53 \pm 0.24$
	4	111	5.72	$2.12 \pm 1.26$	1.40	$1.39 \pm 0.56$	0.94	$0.16\pm0.13$
	5*	110	69.3	$2.29 \pm 0.93$	0.45	$0.91 \pm 0.37$	6.31	$0.22\pm0.10$
	7	105	30.0	$2.62 \pm 1.36$	0.58	$1.27 \pm 1.06$	0.44	$0.59 \pm 0.32$
	8	117	9.81	$1.68\pm0.94$	1.24	$1.13\pm0.69$	0.15	$0.63\pm0.36$
	9	114	30.3	$1.17\pm0.57$	1.69	$3.56 \pm 1.66$	0.11	$0.16\pm0.14$



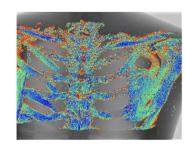


## **Correction of 2D Misalignment**

- The evaluation of the misalignment in the overlay
  - Structures of interest: pre-selected feature points
  - Misalignment measurement for each frame k
    - $\sum \left( dist(p_i^{est,k}, p_i^{GT,k}) \right)$ , where  $dist(\cdot, \cdot)$  is the Euclidean distance
  - Choose the frame with largest projection shift  $\sum (dist(p_i^{I}, p_i^{GT}))$
  - Correction of misalignment from [17.3, 33.2] mm to [1.9, 6.5] mm



[1] Wang et al., Depth-Layer Based Patient Motion Compensation for the Overlay of 3D Volumes onto X-Ray Sequences, BVM, 2013







## **Conclusion & Outlook**

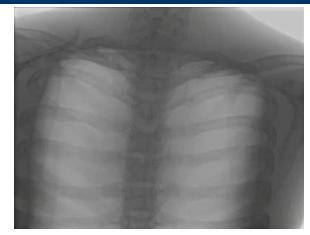


- Conclusion
  - Gradient-based differential 3D motion estimation
  - Mathematical model from 2D motion to 3D differential motion
  - An iteratively re-weighted least square (IRLS) minimization
  - Capable of estimating 3D motion out of 2D tracking
    - over 95% recovery rate for in-plane motion
    - ~80% recovery rate for off-plane longitudinal rotation
  - Correction of misalignment: 8/10 cases under 5 mm (clinical failure threshold [2])
- Outlook
  - Refinement to compensate the approximation error
  - Re-initialization of the features considering 2D/3D correspondence
  - Robustness enhancement
    - More motion models (articulated motion, free form deformation)
    - External disturbance (interventional device, contrast injection)

<sup>[2]</sup> Gendrin et al., Validation for 2D/3D registration II: The comparison of intensity-and gradient-based merit functions using a new gold standard data set, Medical Physics, 2011

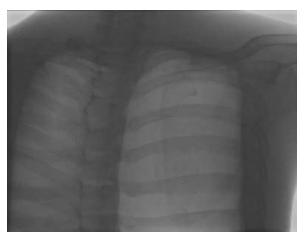
## **3 2014** Thank you for your attention! Poster Session: P2-25

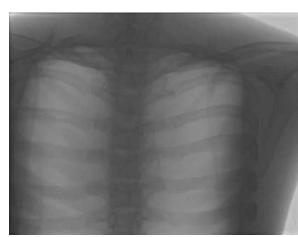






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