

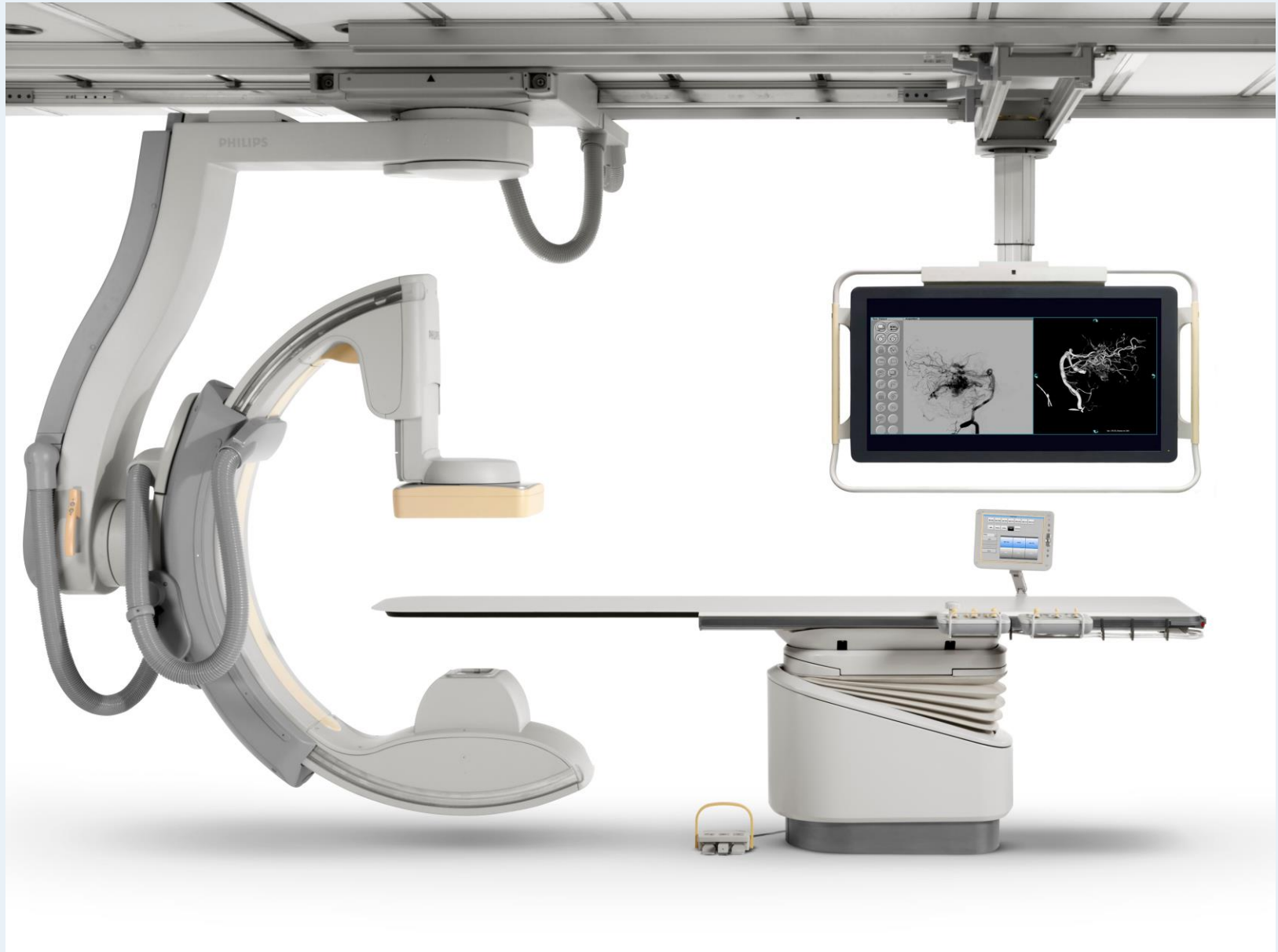
# Cardiac C-arm computed tomography

PhD defense  
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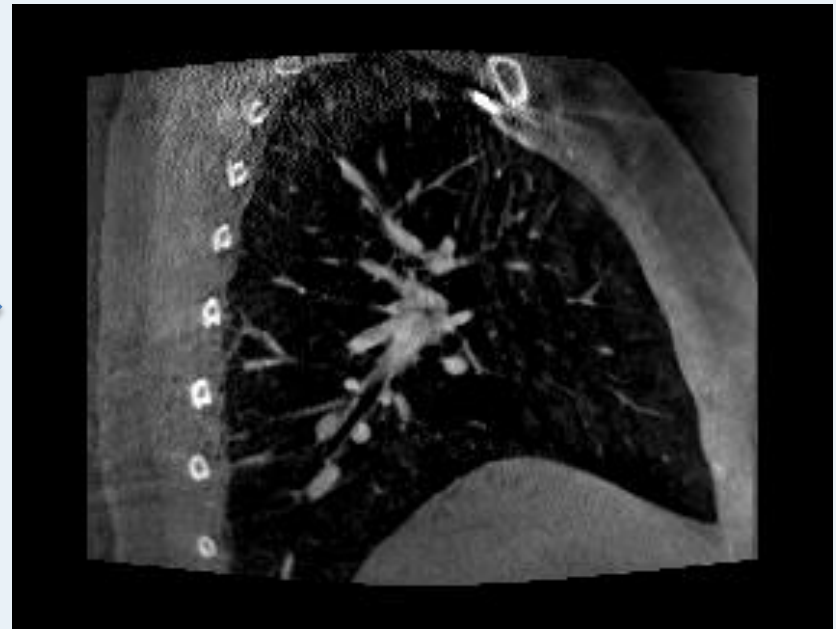
# Introduction What is a C-arm ?



## Projections



## Volume

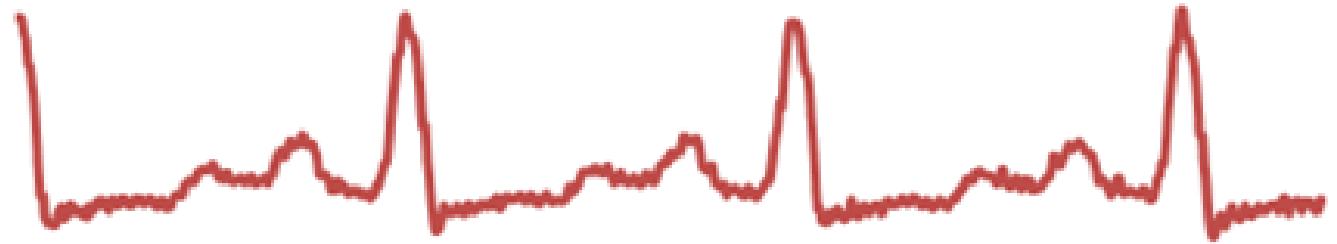


- **Introduction**
  - Two different problems
  - State of the art in cardiac C-arm CT
  - The acquisition protocol
  - Moving Shepp & Logan phantom
  - ECG-gating
  - Angular distribution of projections
  - Artifacts / Blur tradeoff
- **3D compressed sensing**
- **A bit of math**
- **4D compressed sensing**
- **Perspectives**
- **Conclusion**

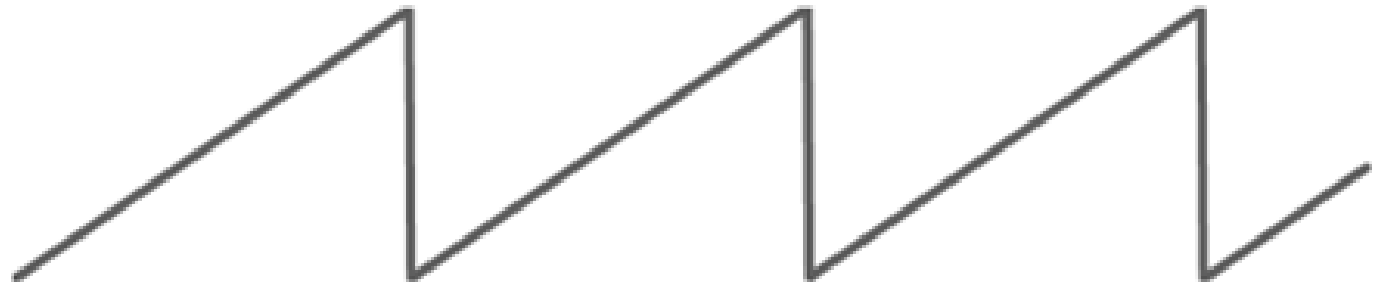
- **Soft tissue analysis**
  - 3D diastole reconstruction
  - Beating motion = trouble
- **Functional analysis**
  - 3D + time reconstruction
  - Whole cardiac cycle
  - Beating motion = information
- **In both cases**
  - Respiratory motion = trouble

=> Apnea

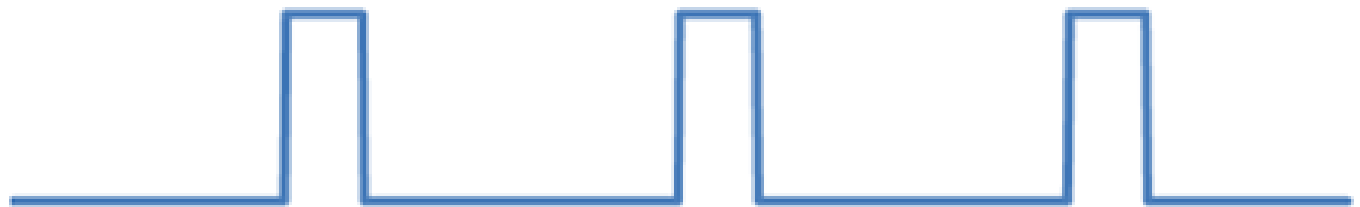
ECG

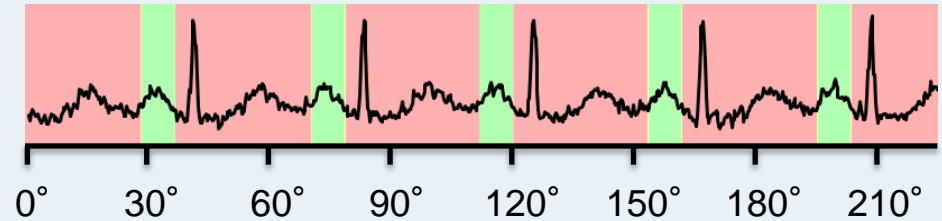
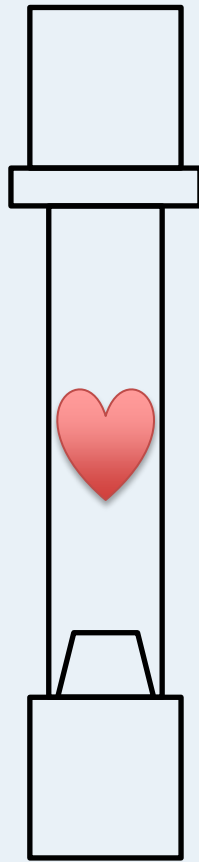


Cardiac phase



Gating weights





- packets of consecutive projections
- Large gaps between packets
- #Packets = #Cardiac cycles in acq.

- Sum of ellipsoids
- Exact line-integral calculation
- Modified to “beat”





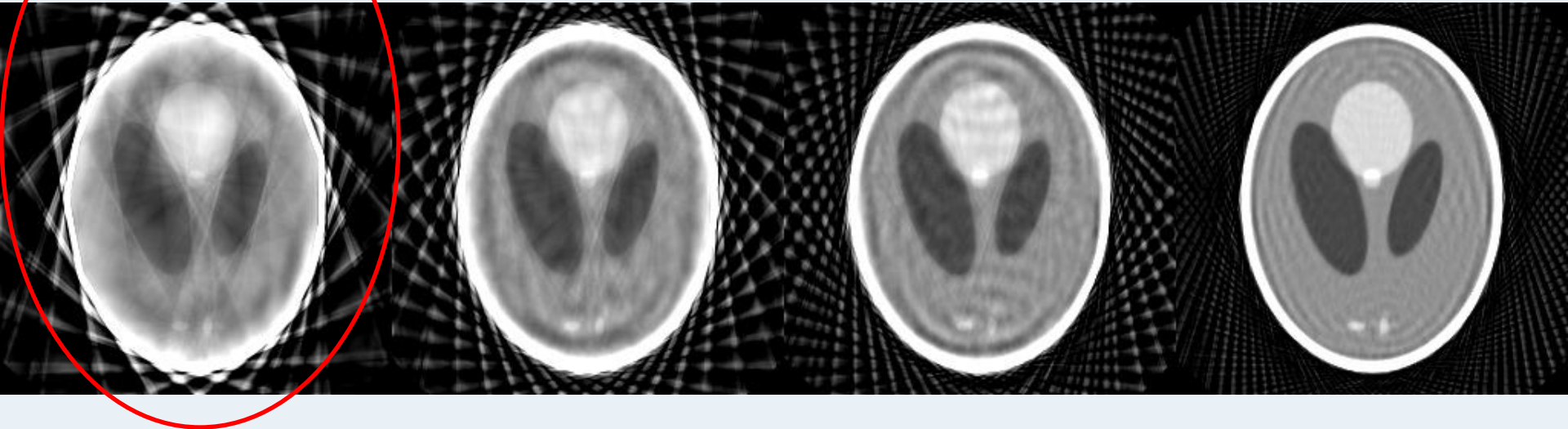
## SART reconstructions from 60 projections, starting from zero

10 packets of  
6 projections

20 packets of  
3 projections

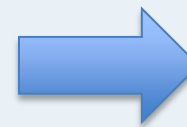
30 packets of  
2 projections

60 "packets" of  
1 projection



**More packets = Less artifacts**

**#Packets = #Cardiac cycles in acquisition**

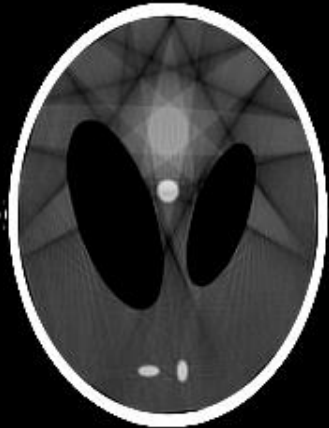


**Fast beating heart**

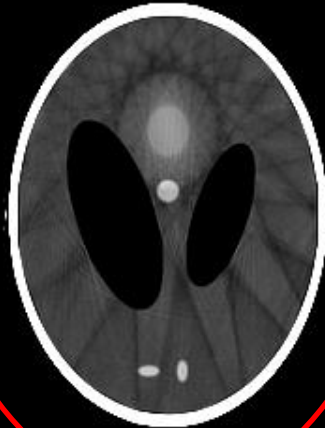
**Long acquisition**

## SART reconstructions from 60 projections, starting from ungated

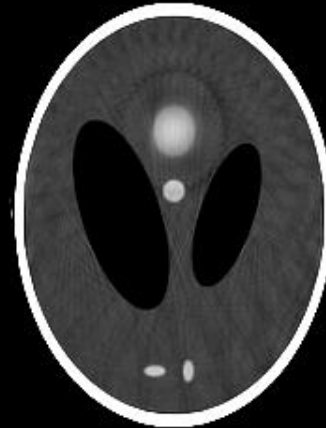
5 packets of  
12 projections



10 packets of  
6 projections



20 packets of  
3 projections

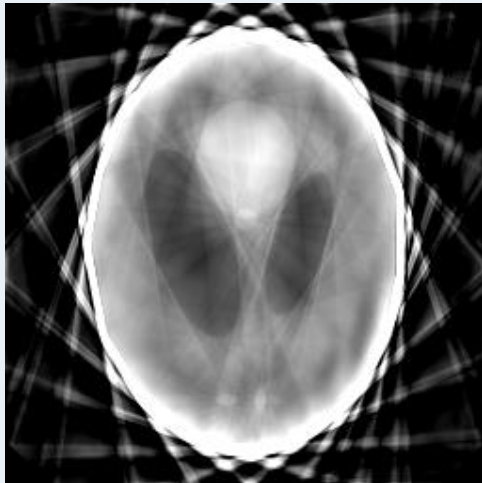


30 packets of  
2 projections

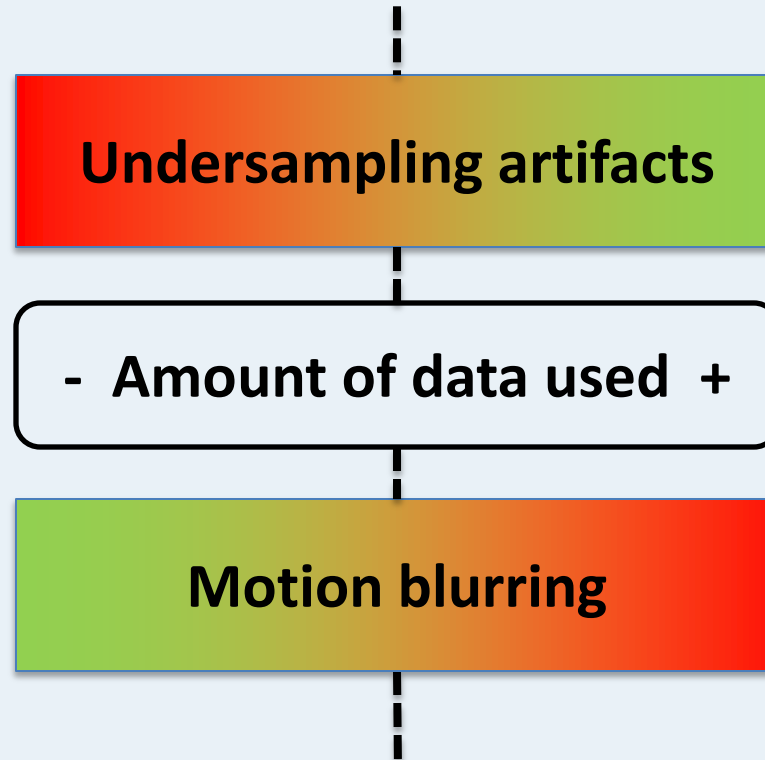
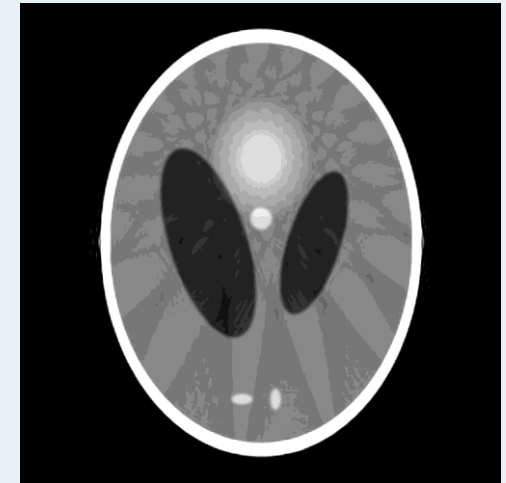


**More packets = Less motion blur**

ECG gated



Ungated



Tradeoff ?

- **Multiple sweep acquisitions**
  - High image quality on a **single** phase
  - Motion-compensated reconstruction techniques
  - High dose
  - Long apnea (at least 12s, in practice around 20s)
  - High amount of contrast
  - Mostly used on animals as of today

Lauritsch, Jan Boese, Lars Wigström, Herbert Kemeth, and Rebecca Fahrig. "Towards Cardiac C-Arm Computed Tomography." *IEEE Transactions on Medical Imaging* 25, no. 7 (July 2006): 922–934.

Prümmer, M., Joachim Hornegger, Guenter Lauritsch, Lars Wigström, Erin Girard-Hughes, and Rebecca Fahrig. "Cardiac C-Arm CT: A Unified Framework for Motion Estimation and Dynamic CT." *IEEE Transactions on Medical Imaging* 28, no. 11 (November 2009): 1836–1849.  
doi:10.1109/TMI.2009.2025499.

Girard, Erin E, Amin Al-Ahmad, Jarrett Rosenberg, Richard Luong, Teri Moore, Günter Lauritsch, Jan Boese, and Rebecca Fahrig. "Contrast-Enhanced C-Arm CT Evaluation of Radiofrequency Ablation Lesions in the Left Ventricle." *JACC. Cardiovascular Imaging* 4, no. 3 (March 2011): 259–268.  
doi:10.1016/j.jcmg.2010.11.019.

## ■ Single sweep acquisitions

- Compressed sensing techniques (ASD-POCS, PICCS)

=> Regularized images

- Long apnea (14s in a 2012 paper) and high heart rate (around 90 bpm)
- High amount of contrast (37 cc for a 10kg swine)

Lauzier, Pascal Thériault, Jie Tang, and Guang-Hong Chen. “Time-Resolved Cardiac Interventional Cone-Beam CT Reconstruction from Fully Truncated Projections Using the Prior Image Constrained Compressed Sensing (PICCS) Algorithm.” *Physics in Medicine and Biology* 57, no. 9 (May 7, 2012): 2461–2476. doi:10.1088/0031-9155/57/9/2461.

Chen, G.-H., P. Theriault-Lauzier, J. Tang, B. Nett, S. Leng, J. Zambelli, Z. Qi, et al. “Time-Resolved Interventional Cardiac C-Arm Cone-Beam CT: An Application of the PICCS Algorithm.” *Medical Imaging, IEEE Transactions on* 31, no. 4 (April 2012): 907–923. doi:10.1109/TMI.2011.2172951.

- **Single breath hold**
- **10.3 seconds**
- **308 projections**
  - 1024 \* 792 pixels
  - 38 cm \* 29 cm
  - 0.74 mm \* 0.74 mm pixels
- **210 ° (short scan)**
- **About 60 cc of iodine**
- **ECG-recording**

**=> Nothing in the literature with similar constraints**

- **Introduction**
- **3D compressed sensing**
  - Augmented Lagrangian + ADMM + total variation
  - Augmented Lagrangian + ADMM + wavelets
  - PICCS
  - Animated sequences
- **A bit of math**
- **4D compressed sensing**
- **Perspectives**
- **Conclusion**

$$\hat{f} = \arg \min_f \|G(Rf - p)\|_2^2 + \alpha TV(f)$$

$R$  is the forward projection operator (Radon or X-ray transform)

$f$  is the volume we seek

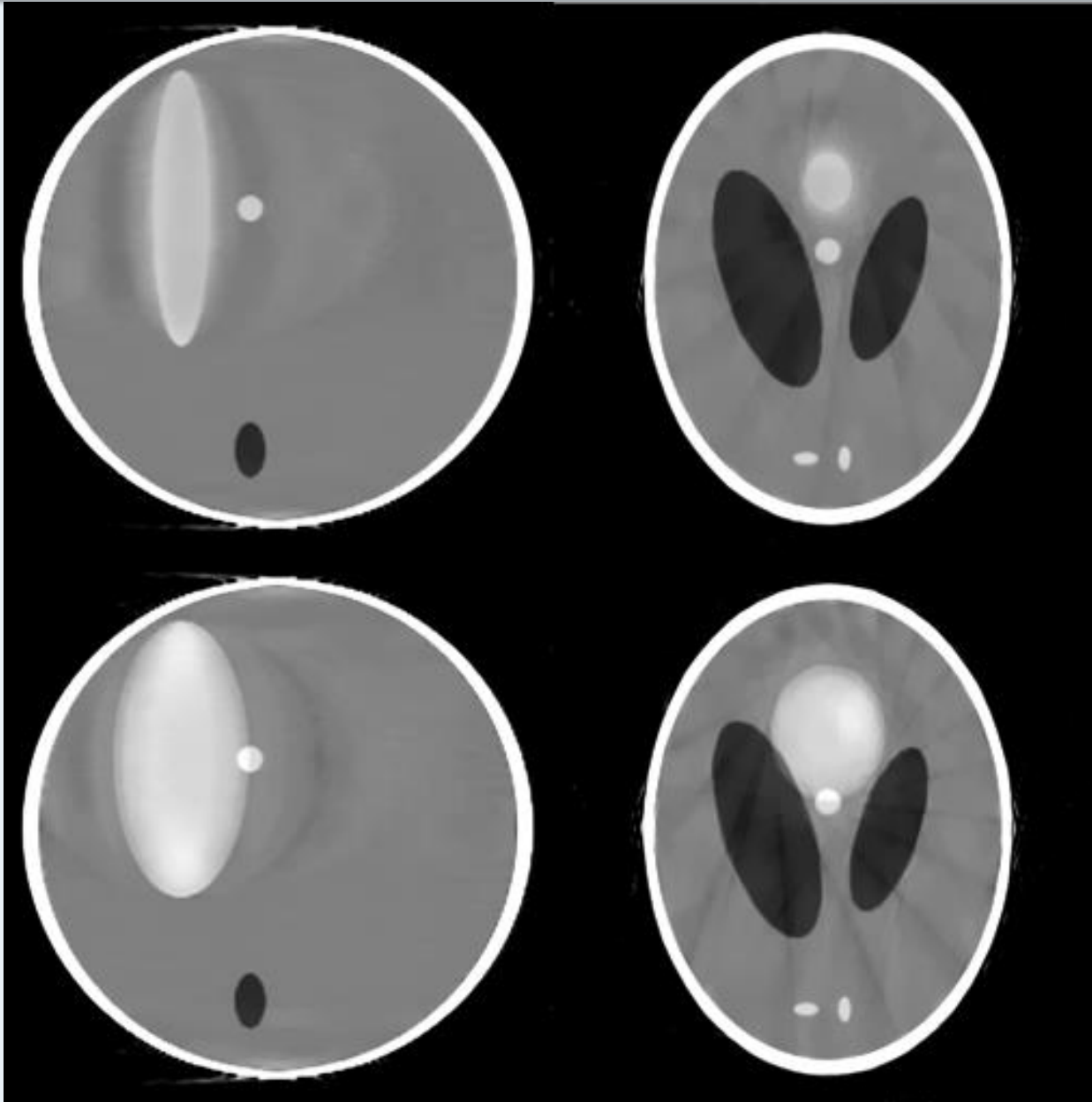
$G$  is the gating operator

$$TV(f) = \sum_{v=1}^V \sqrt{[\nabla_x f(v)]^2 + [\nabla_y f(v)]^2 + [\nabla_z f(v)]^2}$$

- **TV favors piecewise constant images**
- **Real images are not piecewise constant**
- **Regularization must remain limited**



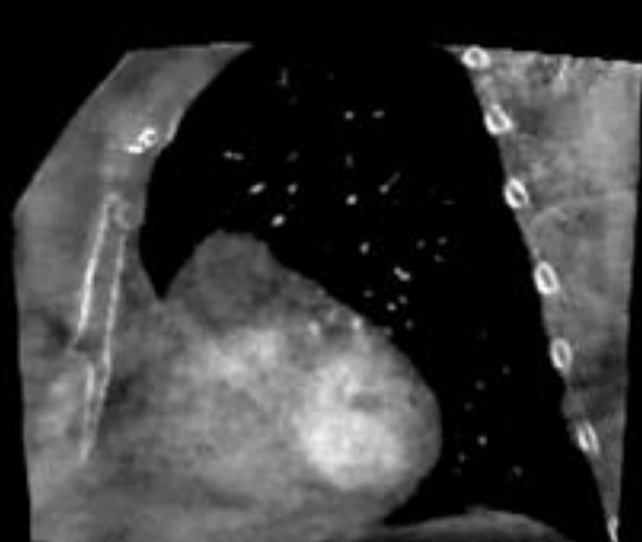
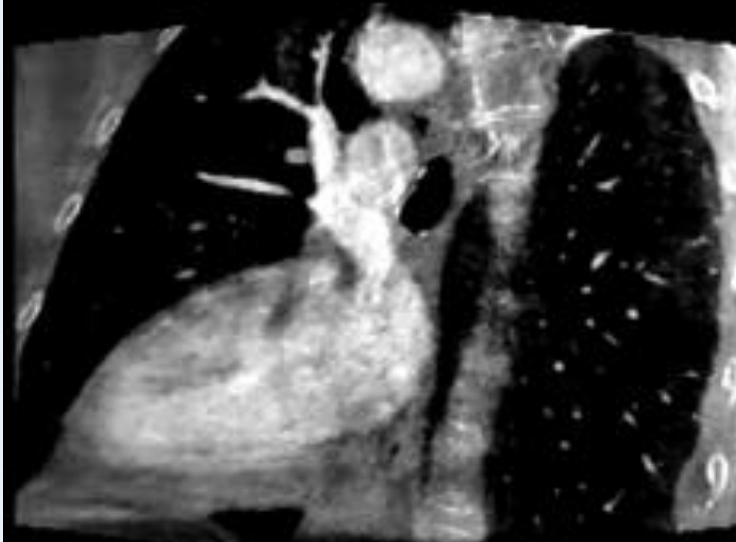
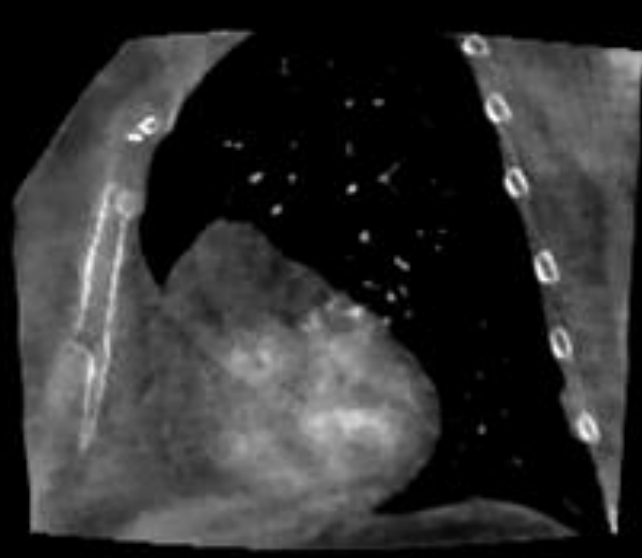
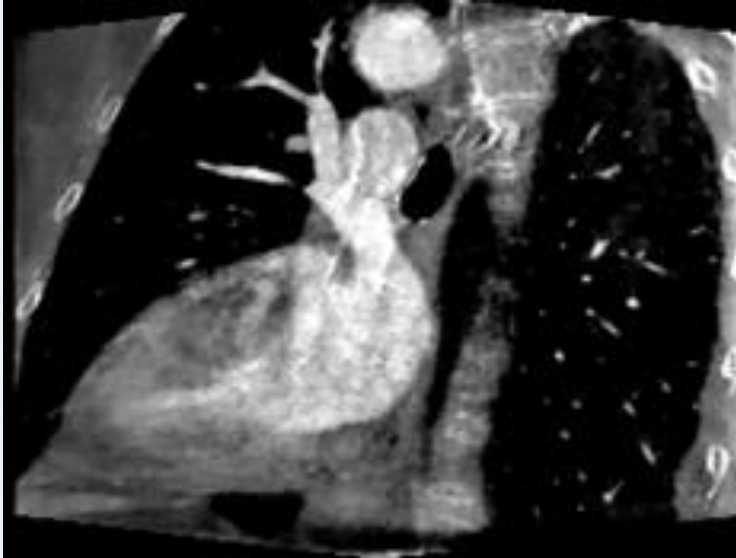
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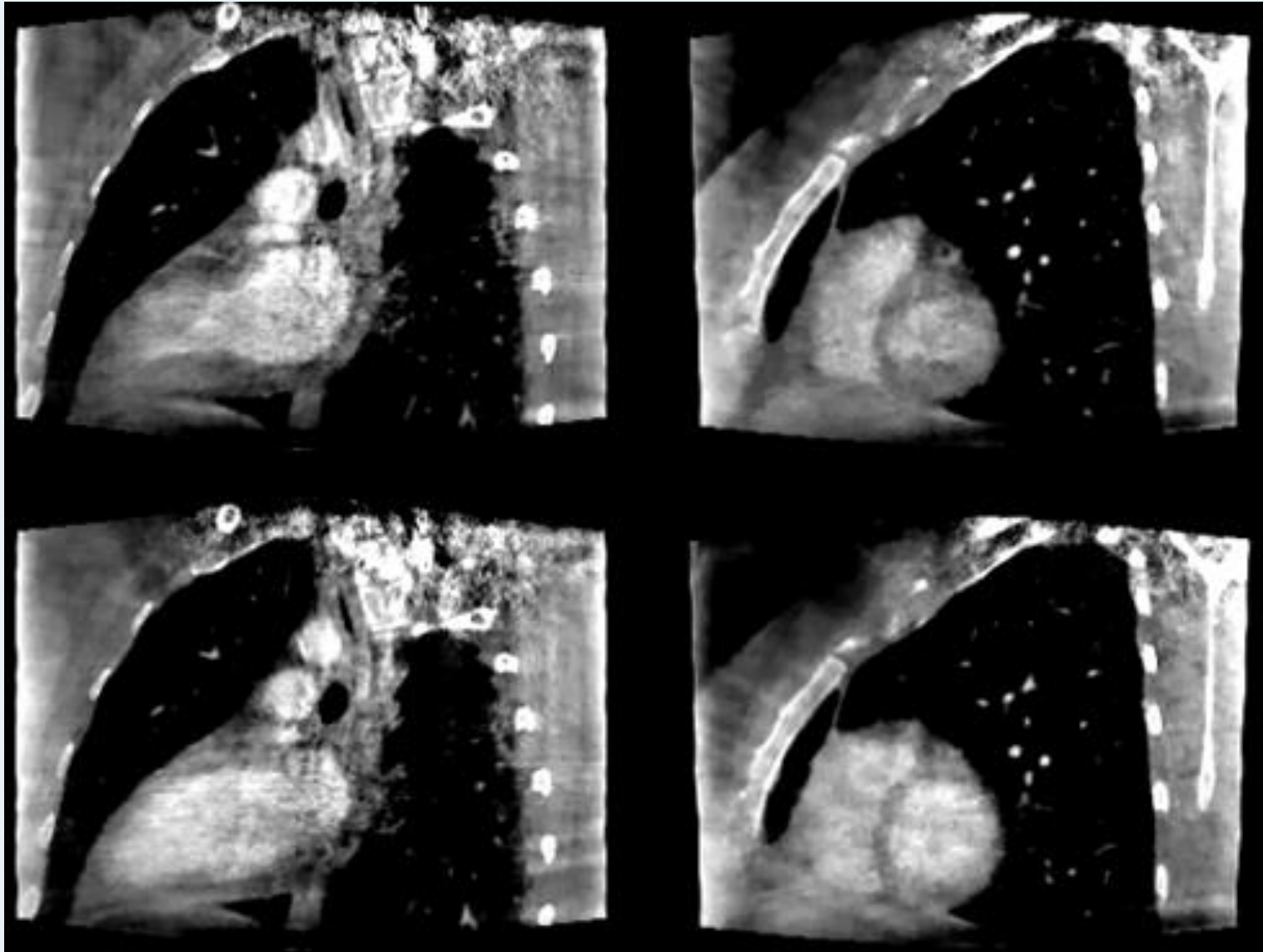
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$$\hat{f} = \arg \min_f \|G(Rf - p)\|_2^2 + \alpha \|Wf\|_1$$

- Daubechies wavelets
- Ineffective on piecewise constant phantoms
- Well suited to real images
- Regularization can be strong

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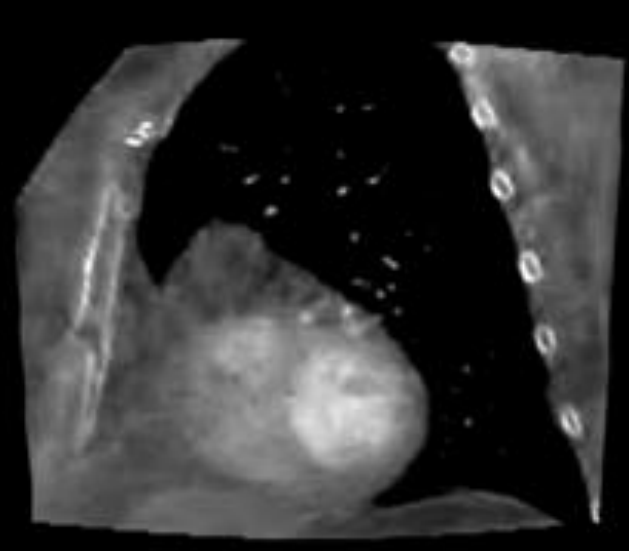
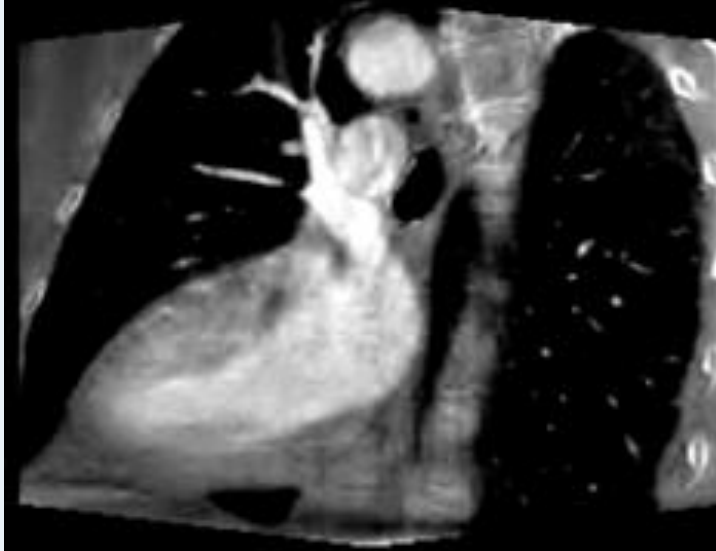
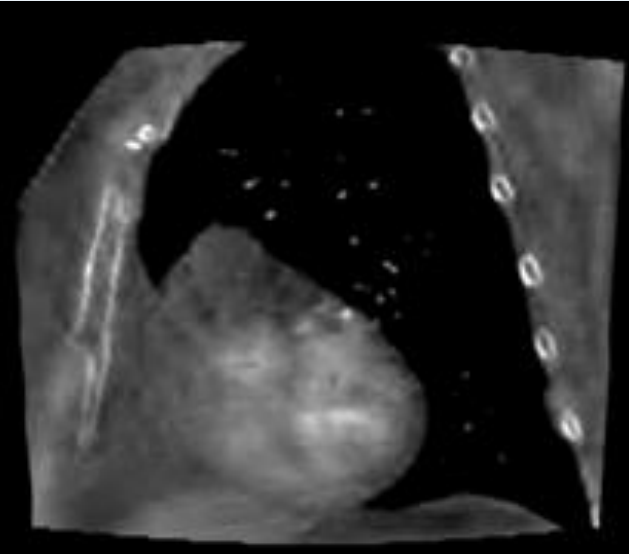
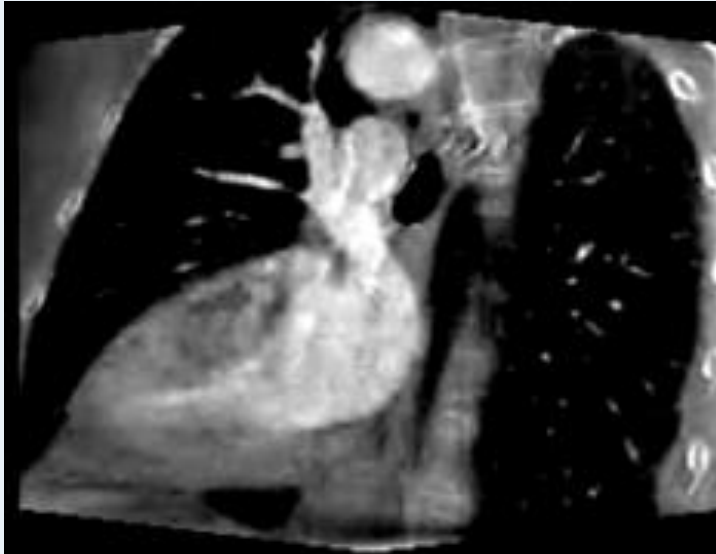
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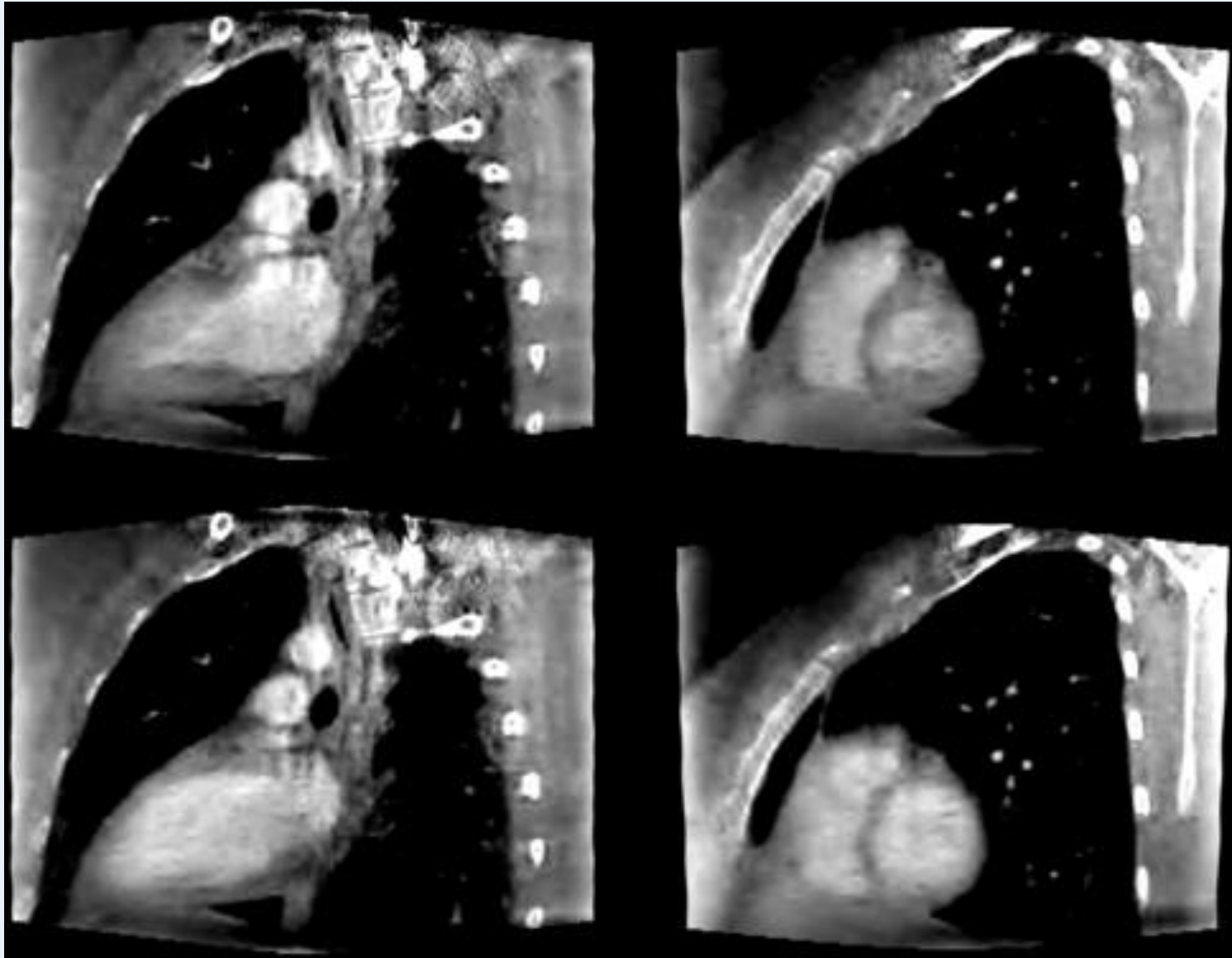




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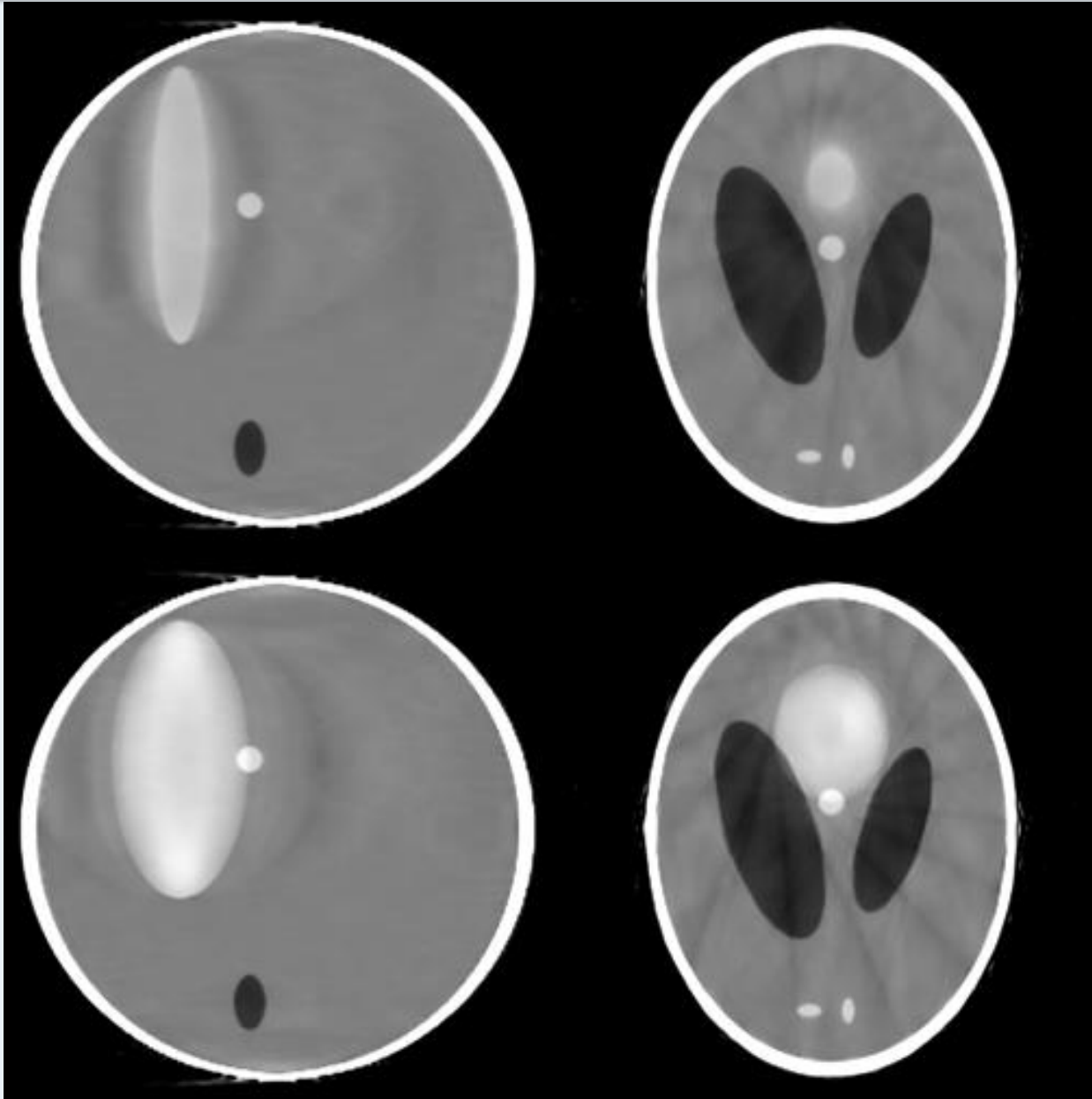


$$\hat{f} = \arg \min_f \mu \|G(Rf - p)\|_2^2 + (1 - \alpha)TV(f) + \alpha TV(f - f^*)$$

- **Prior Image Constrained Compressed Sensing**
- **State-of-the-art method**
- **SART to minimize data-attachment**
- **Steepest descent for TV minimization**
- **Prior = ungated FDK**
- **No texture-erasing effect**



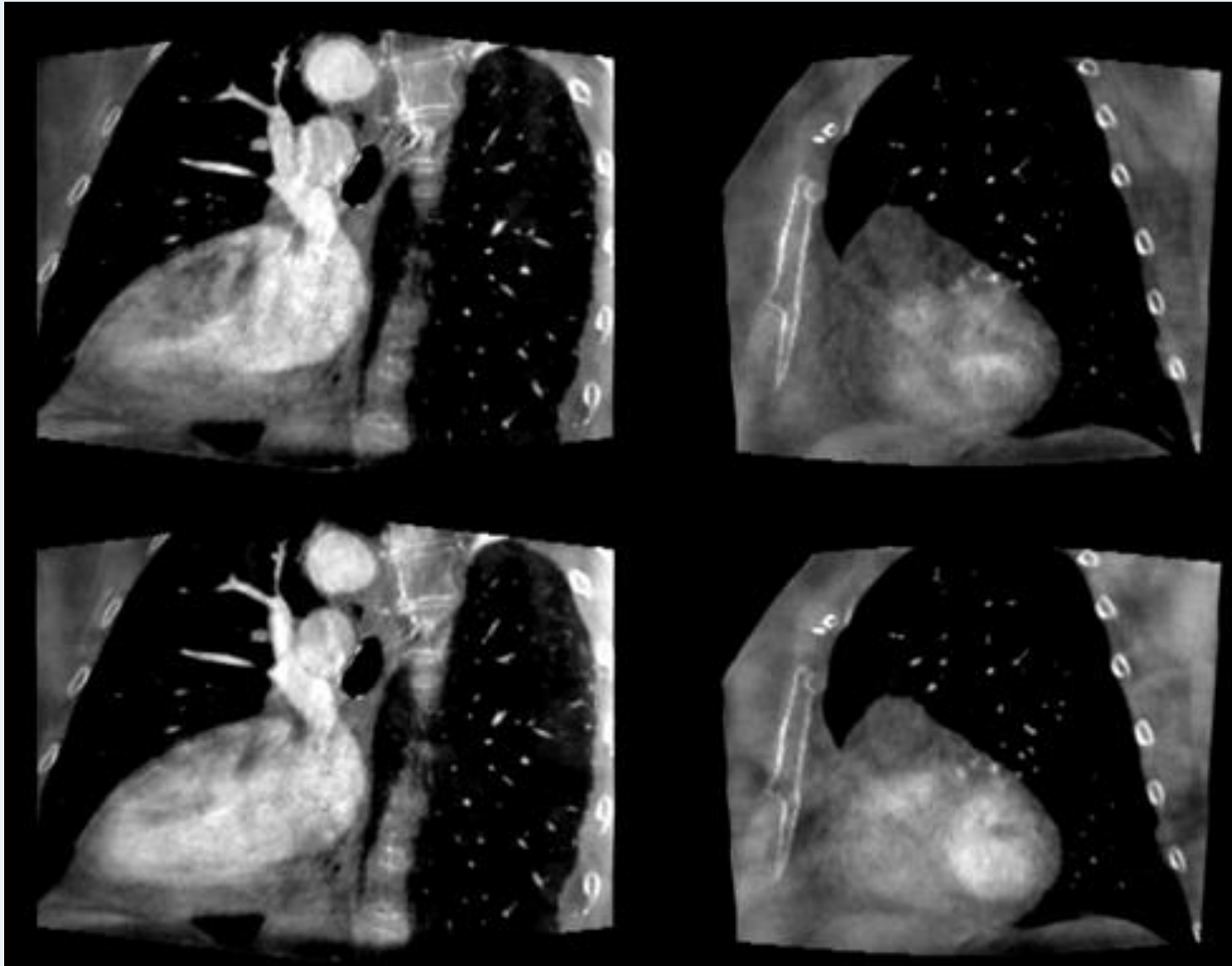
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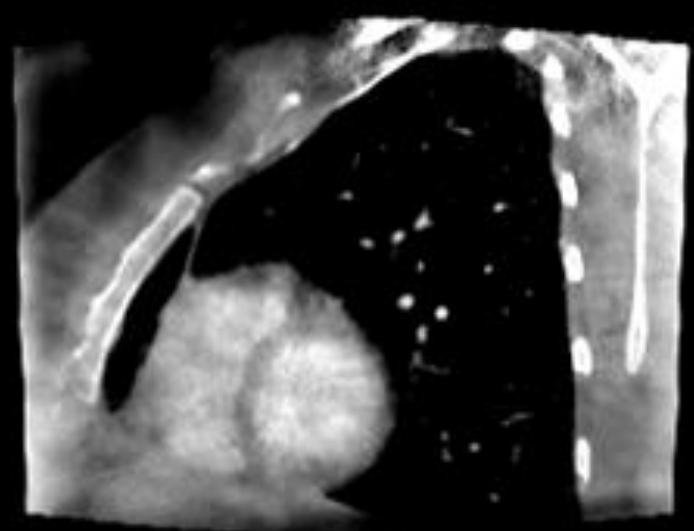
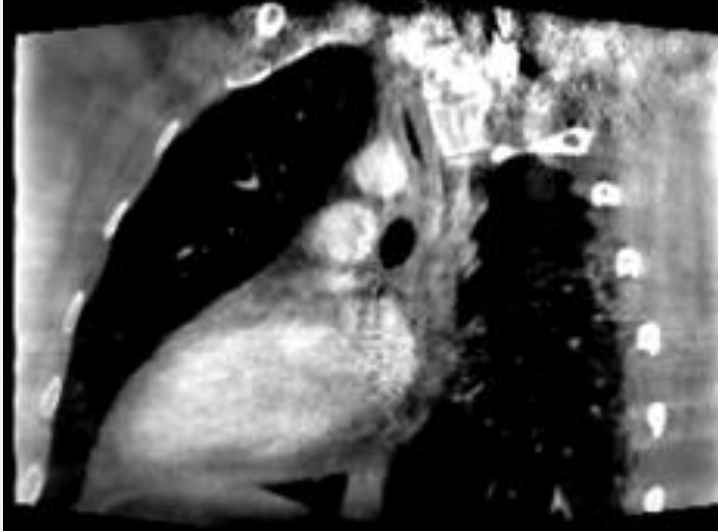
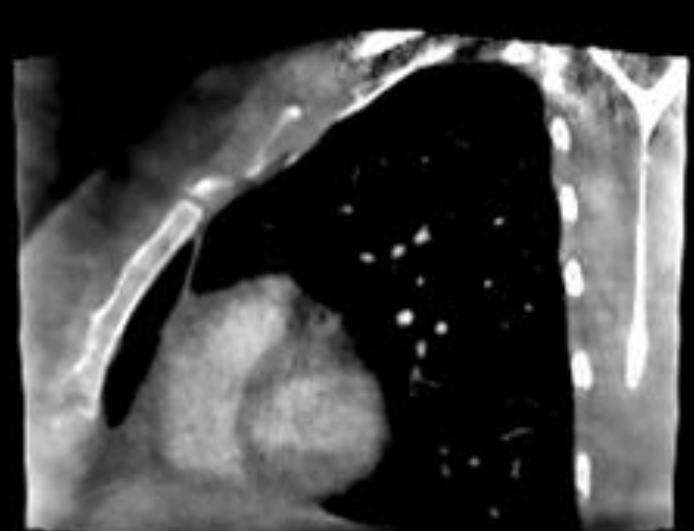
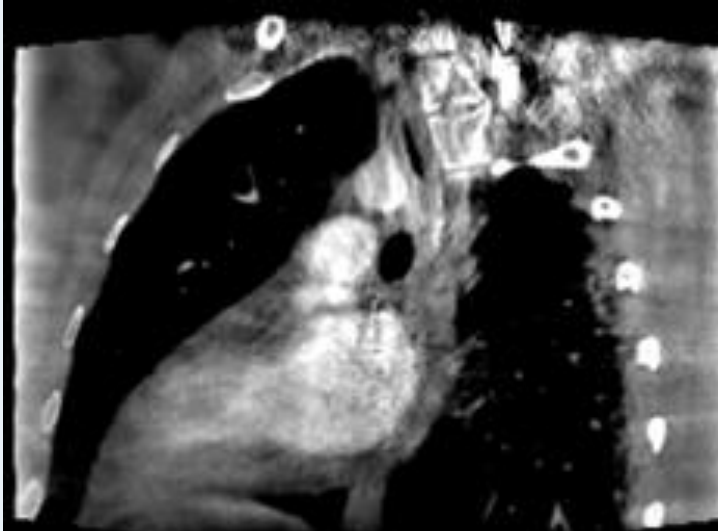
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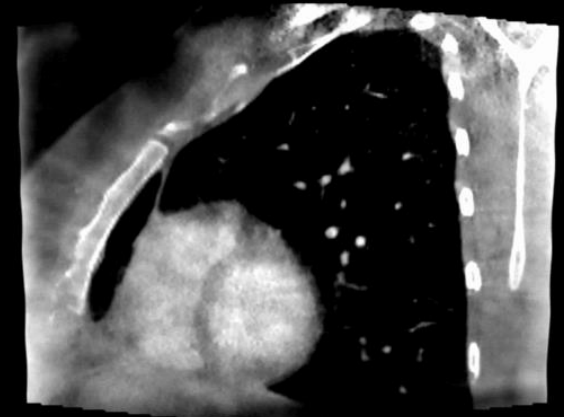
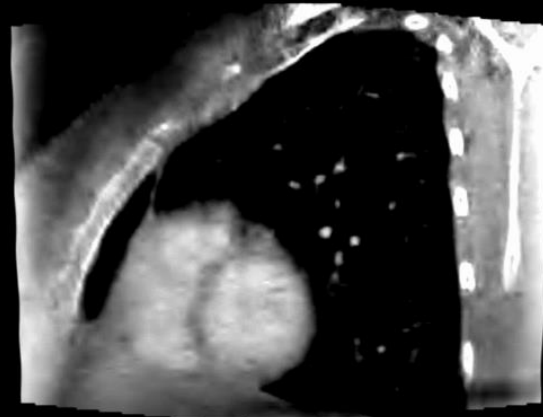
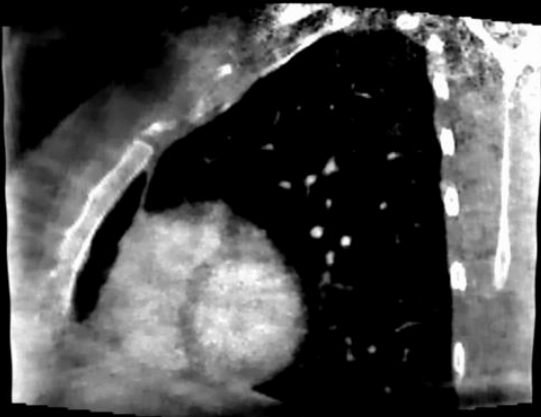
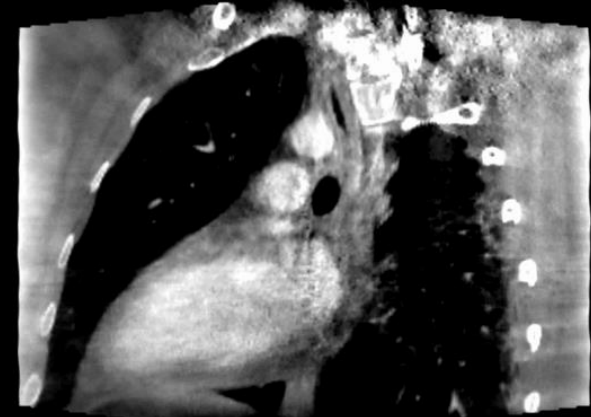
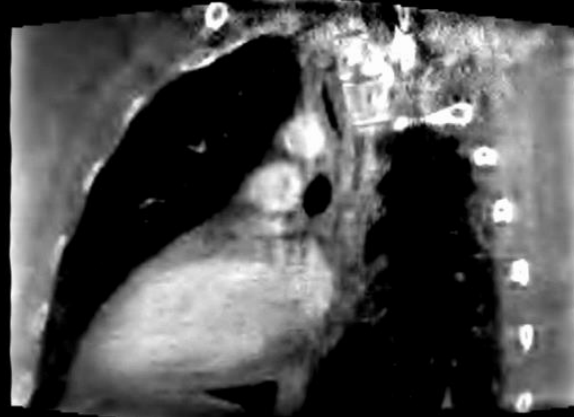
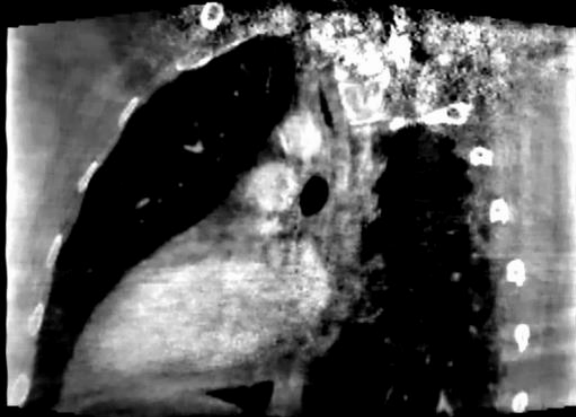
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## ADMM 3D TV

## ADMM 3D Wavelets

## PICCS



- **Introduction**
- **3D compressed sensing**
- **A bit of math**
  - On kernels
  - More on kernels
  - Initialization and regularization
- **4D compressed sensing**
- **Perspectives**
- **Conclusion**

$$\hat{f} = \arg \min_f \|Rf - p\|_2^2$$

$$f = P_{Ker(R)}(f) + P_{Ker(R)^\perp}(f) = f_{Ker} + f_\perp$$

$$Rf = Rf_{Ker} + Rf_\perp = Rf_\perp$$

$\Rightarrow f_{Ker}$  **does not drive the search for  $\hat{f}$**

$$\hat{f} = \arg \min_f \|Rf - p\|_2^2$$

$$\nabla \|Rf - p\|_2^2 = 2R^T(Rf - p)$$

$$\text{Im}(R^T) \subset \text{Ker}(R)^\perp$$

⇒ Gradient descent does not even modify  $f_{\text{Ker}}$

⇒ Same for conjugate gradient

$$\hat{f} = \arg \min_f \|G(Rf - p)\|_2^2$$

$$\hat{f} = \arg \min_f \|GRf - Gp\|_2^2$$

*Ker*(GR) is huge



- **20% gating window**
  - 4 times more information in  $f_{Ker}$  than in  $f_{\perp}$
  - A good  $f_{Ker}$  is crucial
- **Initialization**
  - $f_{Ker}$  remains in its initial state throughout iterations
- **Regularization**
  - Updates  $f_{Ker}$  from  $f_{\perp}$
  - More regularization = better reconstruction of motion

- **Introduction**
- **3D compressed sensing**
- **A bit of math**
- **4D compressed sensing**
  - Augmented Lagrangian + ADMM + TV
  - 4D ROOSTER
  - Animated sequences
- **Perspectives**
- **Conclusion**

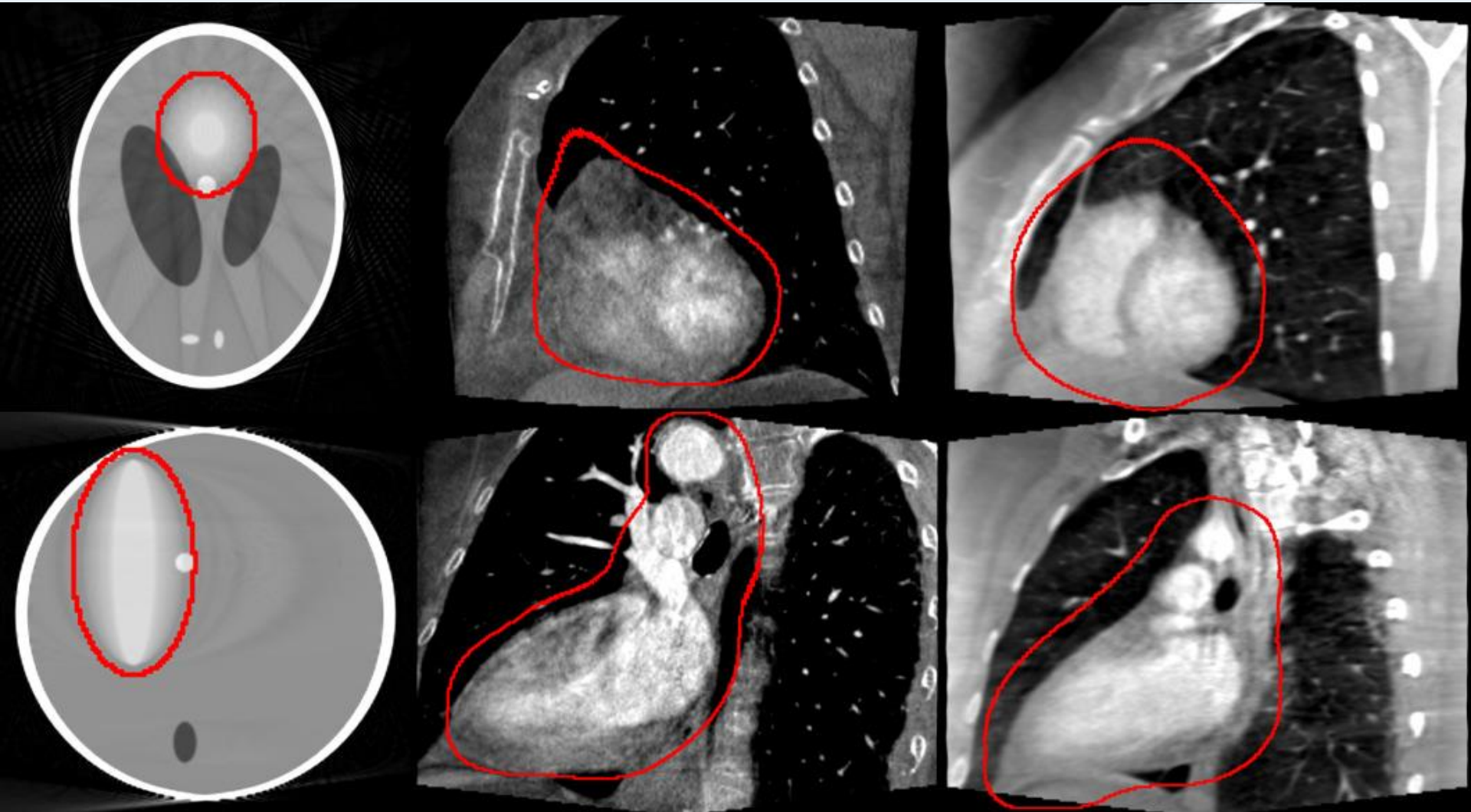
$$\hat{f} = \arg \min_f \sum_{\theta} \|R_{\theta} S_{\theta} f - p_{\theta}\|_2^2 + \alpha ROI\_TV(f)$$

- $f$  : 4D sequence of volumes
- $R_{\theta}$  : projection operator, source at angle  $\theta$
- $S_{\theta}$  : linear interpolation operator
- $p_{\theta}$  : measured projection, source at angle  $\theta$
  
- **Example, with a 4D sequence of 10 phases**
  - Projection  $p_{\theta_0}$  was acquired at 87% of the cardiac cycle
  - $S_{\theta_0}$  will interpolate between phase 80% and phase 90%
  - $S_{\theta_0} f = 0.3f_8 + 0.7f_9$

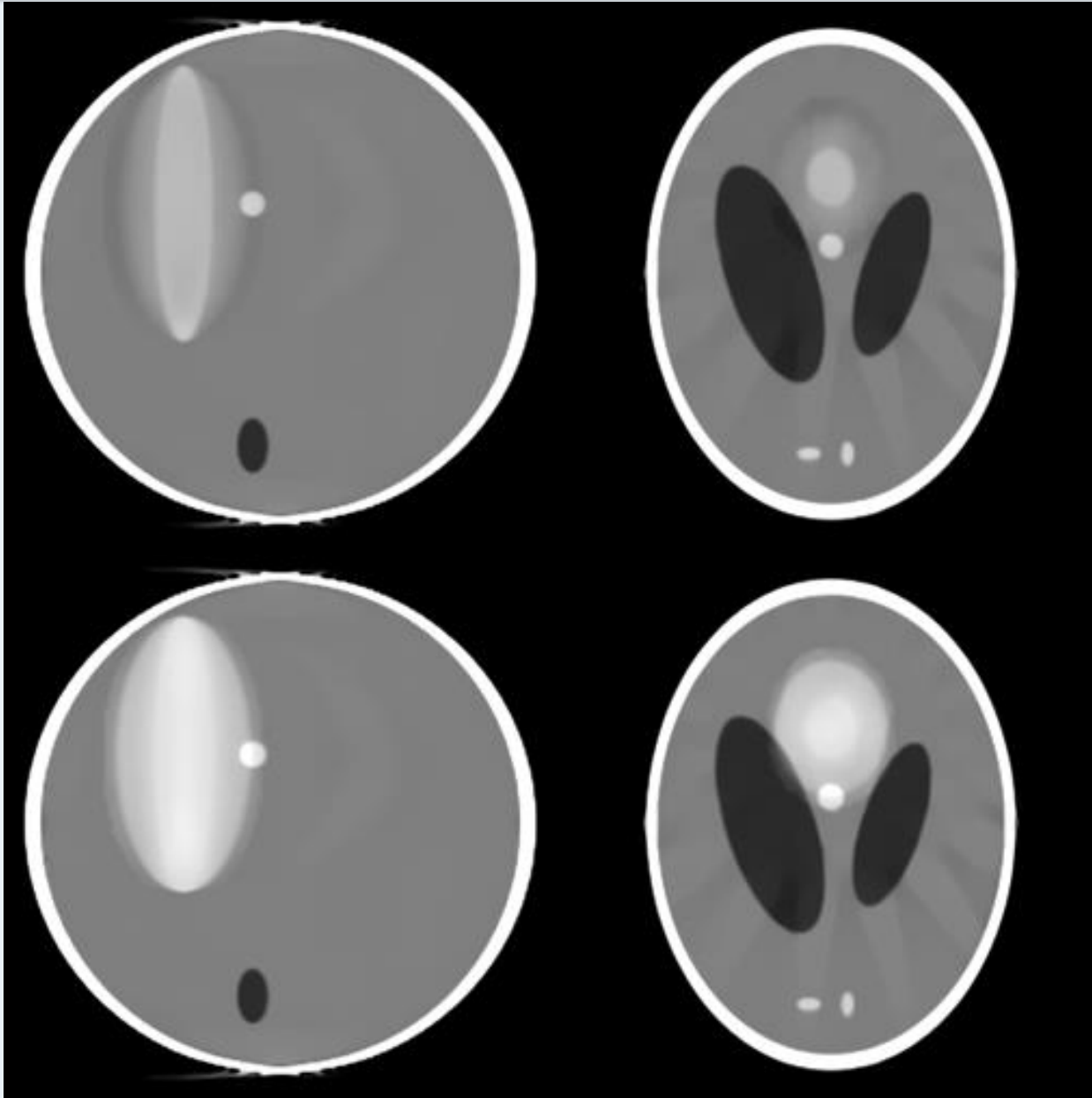
$$\hat{f} = \arg \min_f \sum_{\theta} \|R_{\theta} S_{\theta} f - p_{\theta}\|_2^2 + \alpha ROI\_TV(f)$$

$$ROI\_TV(f) = \sum_{m=1}^M \sqrt{[\nabla_x f(m)]^2 + [\nabla_y f(m)]^2 + [\nabla_z f(m)]^2 + [\omega(m) \nabla_t f(m)]^2}$$

- $\omega(m)$ : motion weighting, high outside ROI, low inside



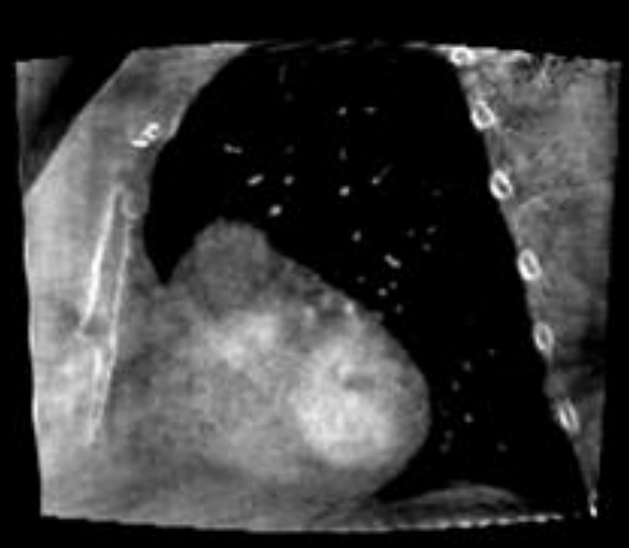
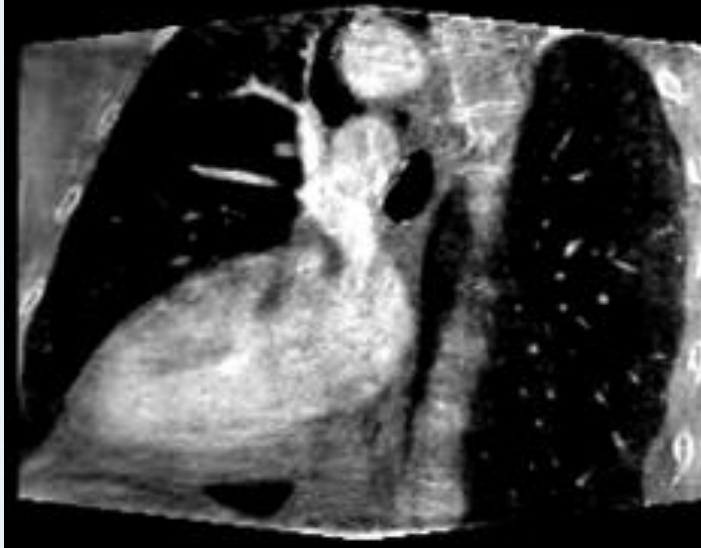
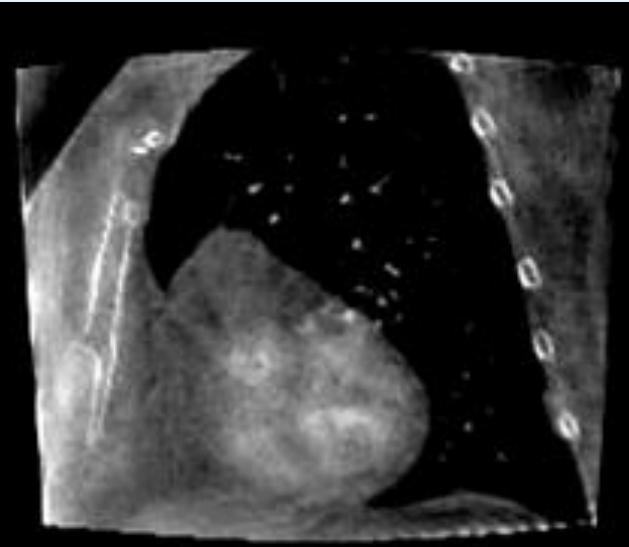
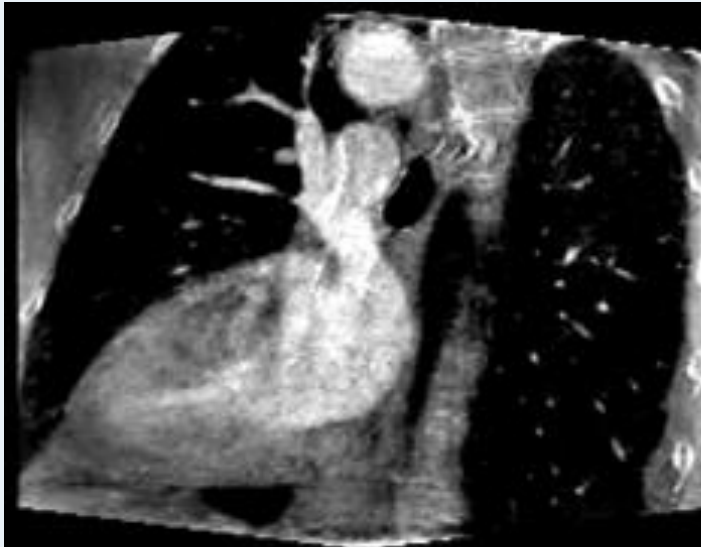
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## Long axis

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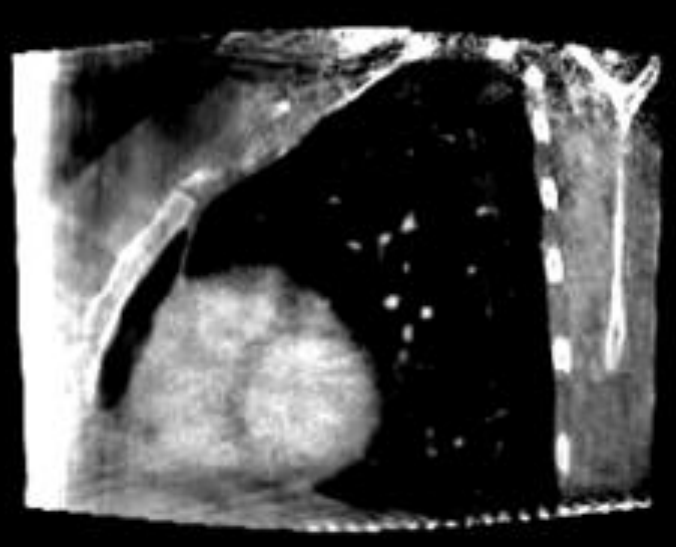
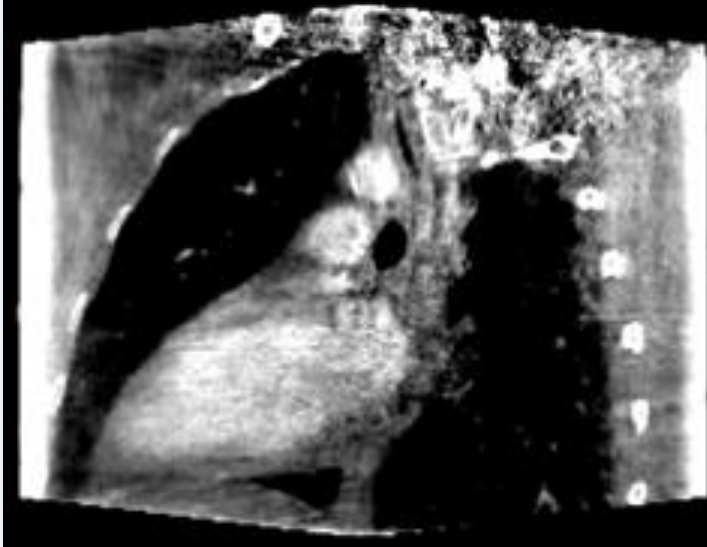
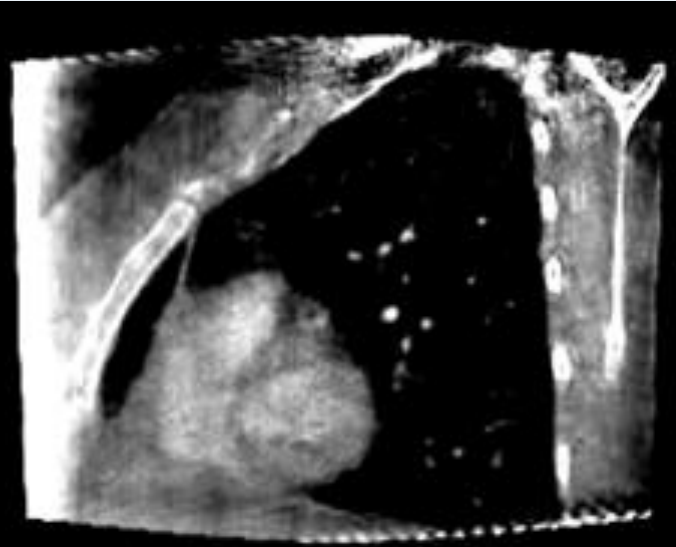
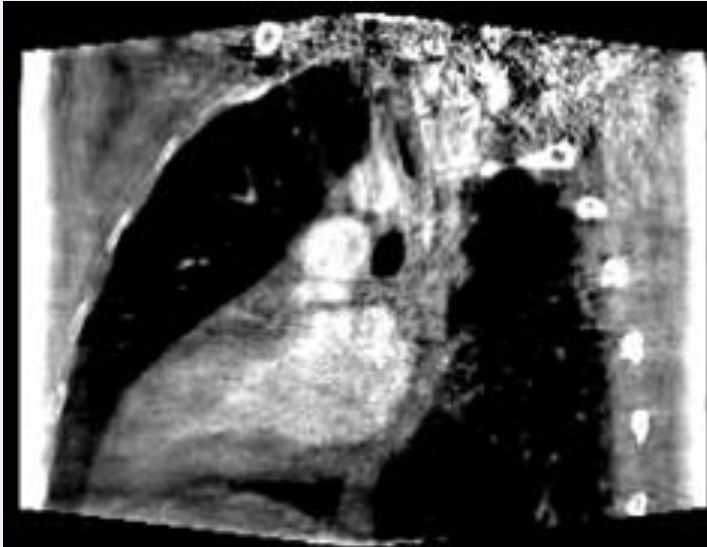




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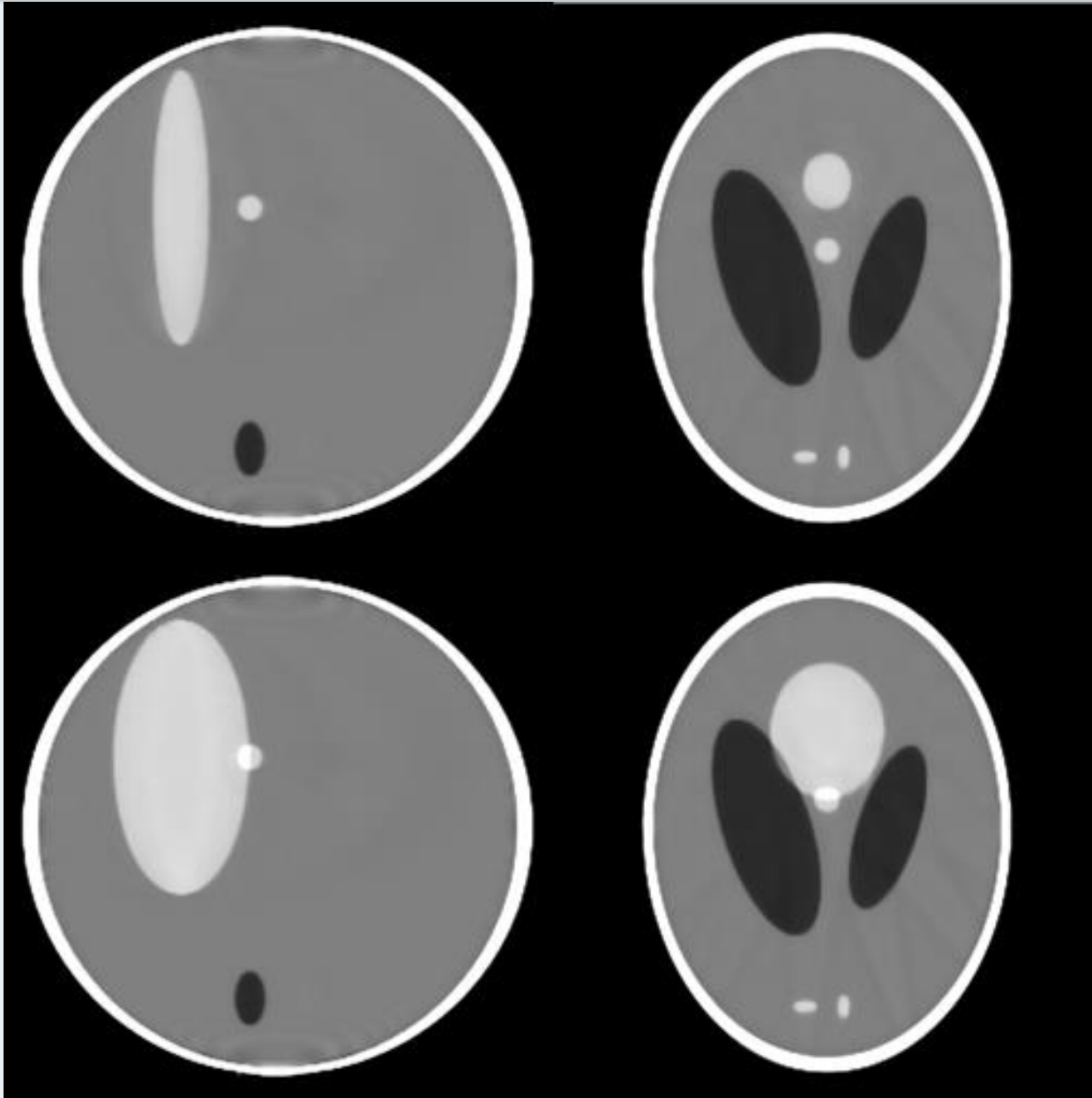


## 4D ReCOnstructiON using SPatial and TEmporal RRegularization

- For iter = 1 to max\_iter

- Conjugate gradient on  $\sum_{\theta} \|R_{\theta} S_{\theta} f - p_{\theta}\|_2^2$
- Positivity enforcement
- Averaging along time outside ROI
- Spatial TV minimization
- Temporal TV minimization

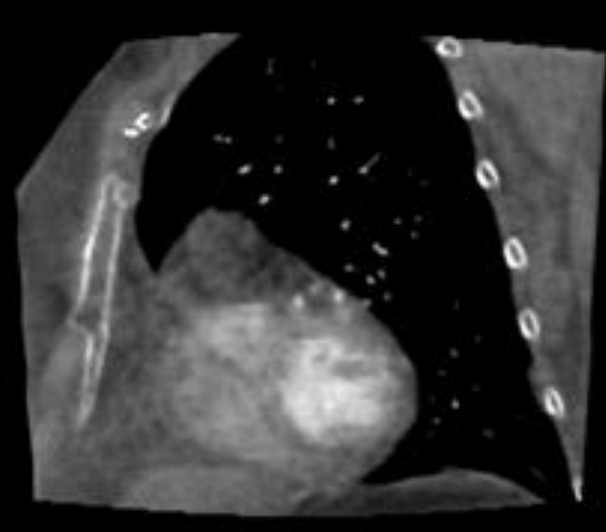
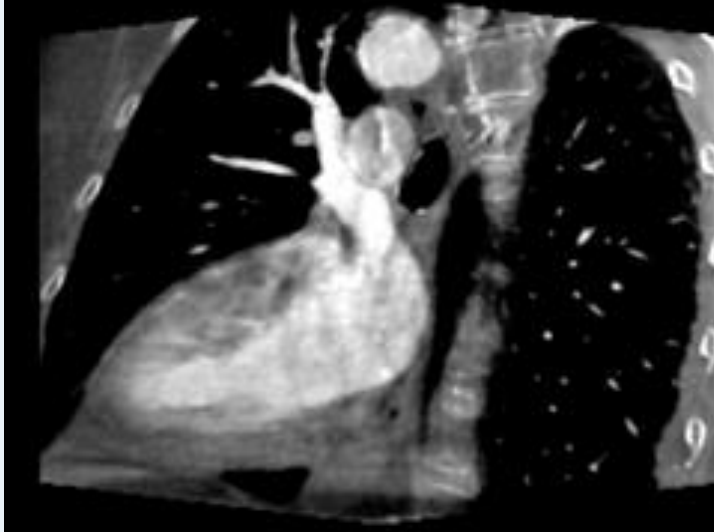
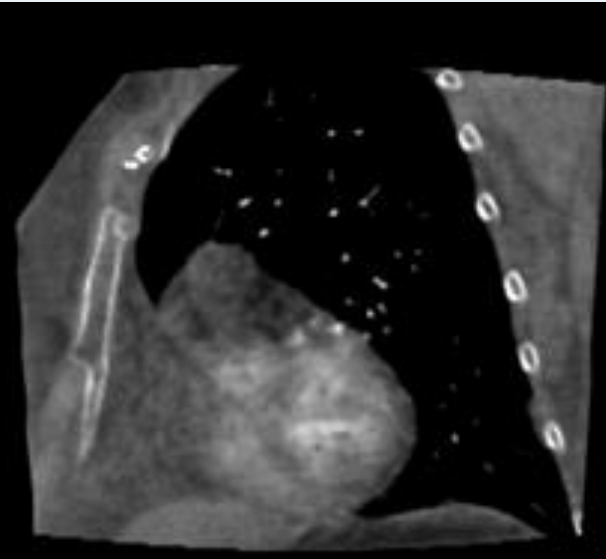
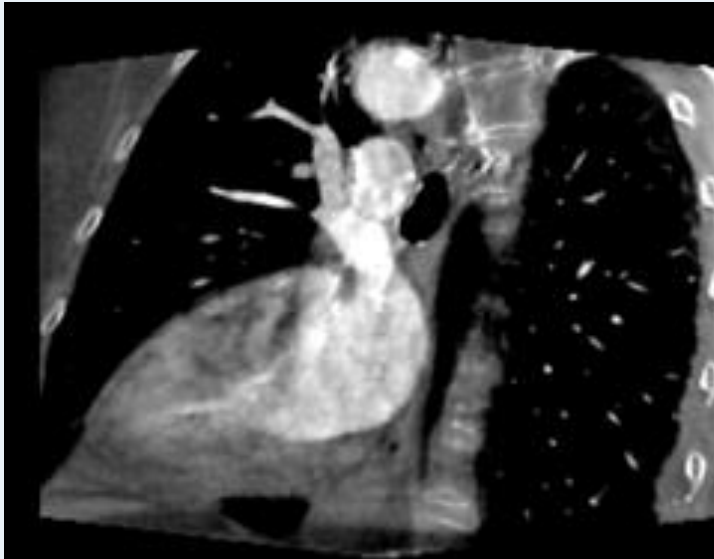
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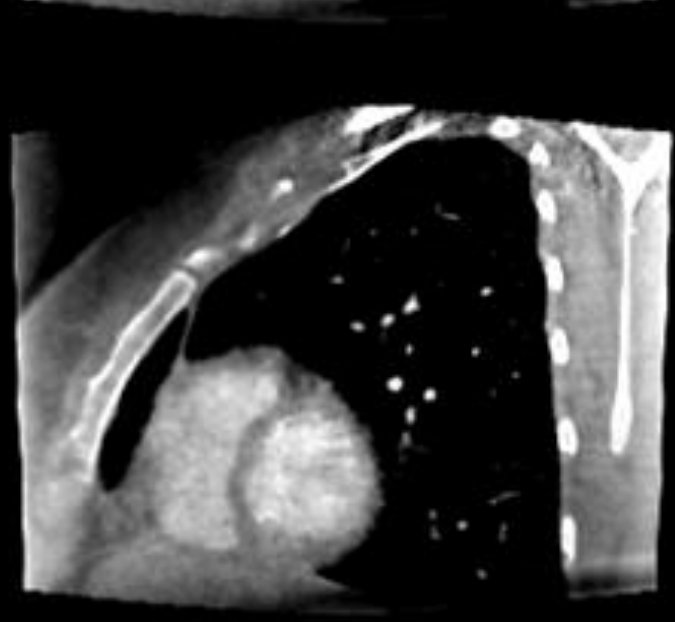
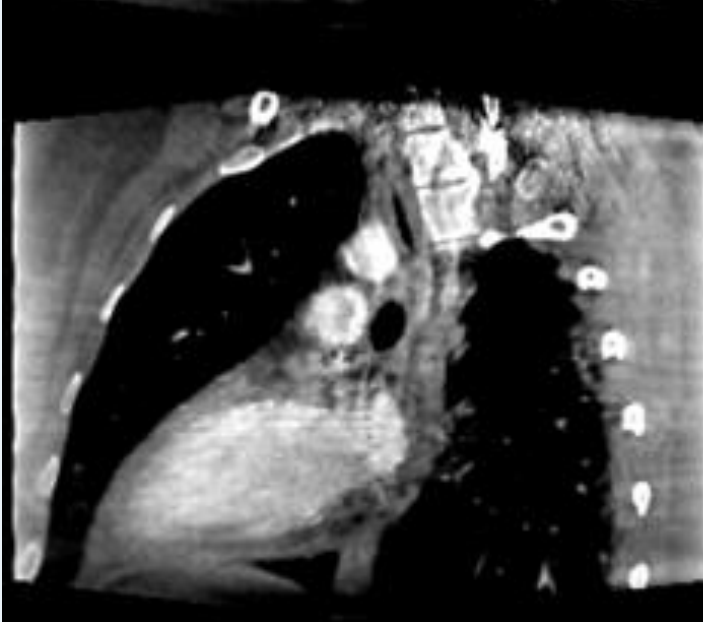
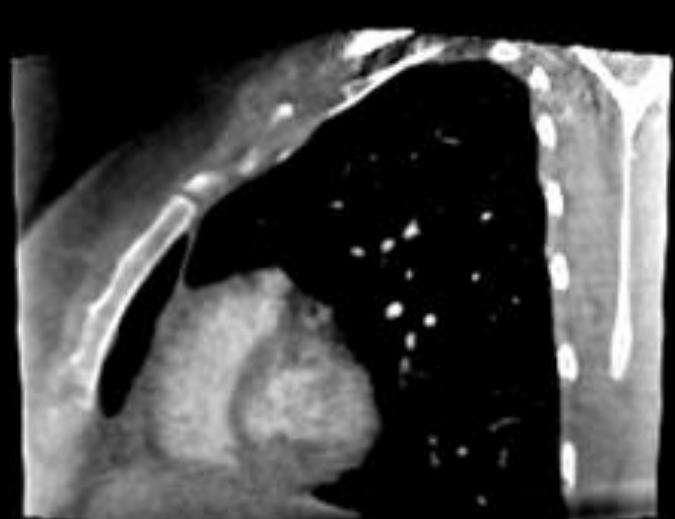
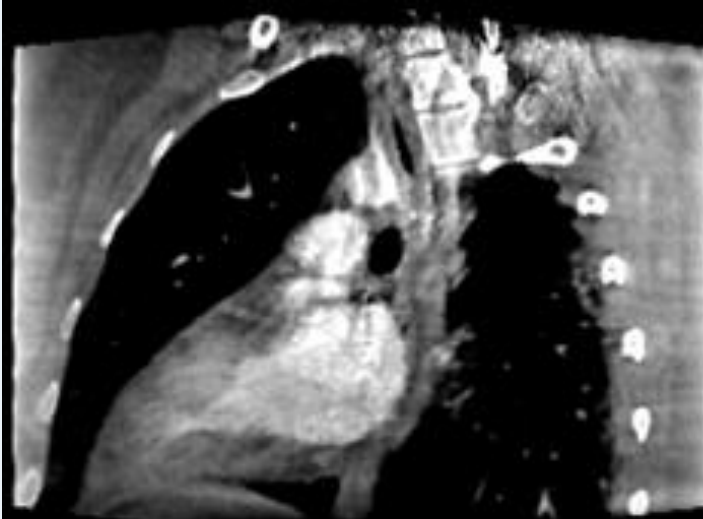
S  
Y  
S  
T  
O  
L  
E  
  
D  
I  
A  
S  
T  
O  
L  
E



Long axis

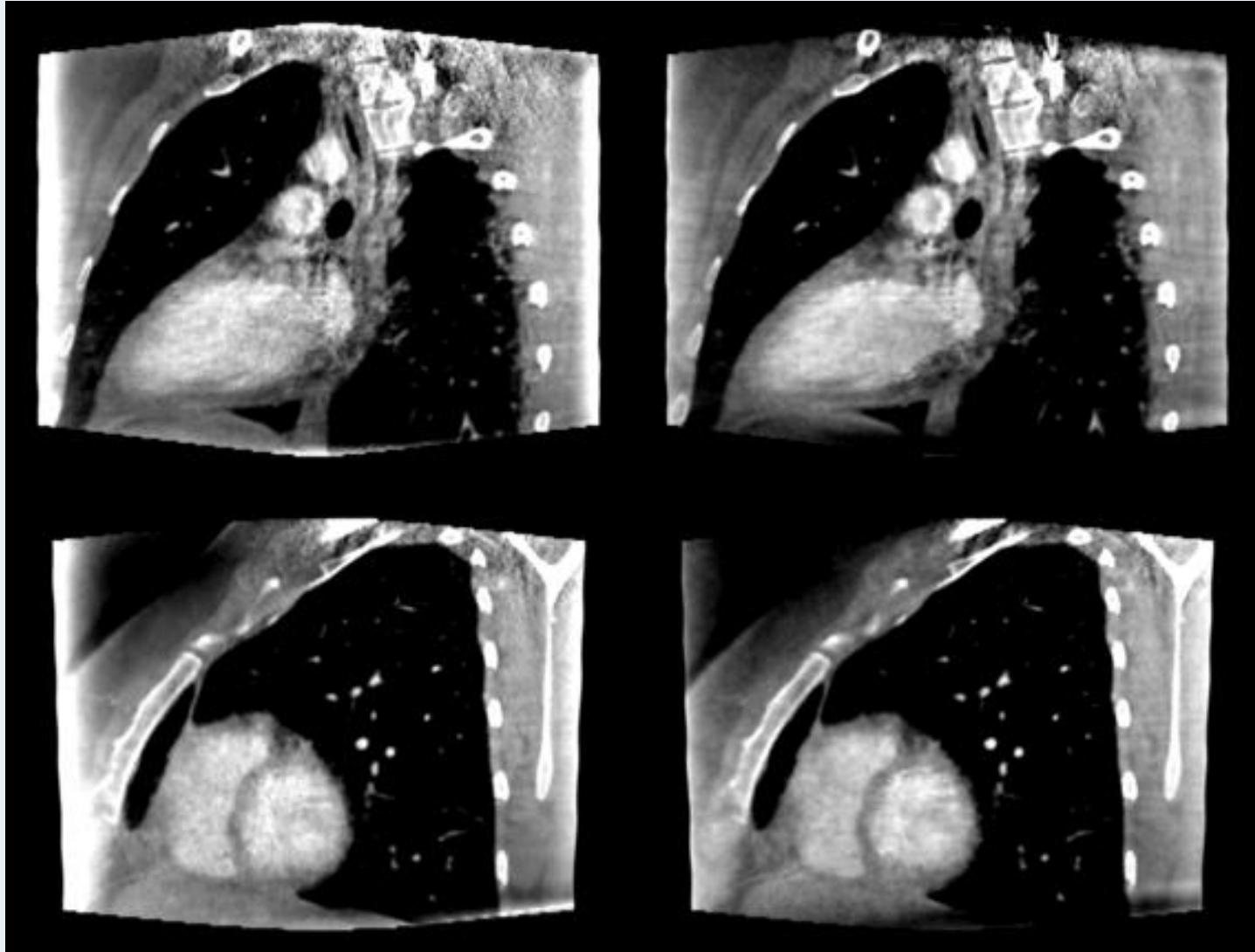
Short axis

S  
Y  
S  
T  
O  
L  
E  
  
D  
I  
A  
S  
T  
O  
L  
E



## ADMM 4D TV

## 4D ROOSTER



- **Introduction**
- **3D compressed sensing**
- **A bit of math**
- **4D compressed sensing**
- **Perspectives**
  - The 4D ROOSTER method
  - Clinical use
- **Conclusion**

- **Other regularization methods**
  - Spatial TV => Wavelets
  - Temporal Non-Local Means
  
- **Fully automatic heart segmentation**
  - Currently performed manually (semi-automatic tool)
  
- **Improve performance**
  - Already implemented in CUDA
  - Can probably be optimized

- **Online processing for injected data**
  - Requires a prototype
  
- **Offline processing for late enhancement**
  - Disappointing
  
- **Compressed sensing in cardiac MRI**
  - Replace projection by Fourier transform
  
- **Free-breathing thorax imaging**
  - Replace ECG-gating by respiratory gating



- Introduction
- 3D compressed sensing
- A bit of math
- 4D compressed sensing
- Perspectives
- Conclusion
  - Improvement over PICCS
  - Take-home messages

- **PICCS is the current state of the art in cardiac C-arm CT**
  - Results published only on animals
  - Our study demonstrates PICCS on human cardiac C-arm CT
  
- **4D ROOSTER outperforms PICCS**
  - No motion outside the heart
  - Consistent motion inside the heart
  - Sharper edges
  - Lower noise

## Limited data ?

- Try to reduce the number of unknowns
- Use compressed sensing iterative methods
- Regularize as much as possible
- Initialize carefully
- Test by starting from zero

**Thank you for you attention**