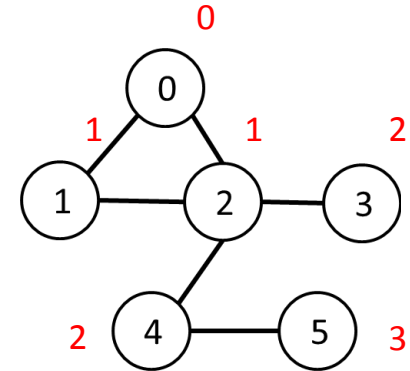


CS 179: GPU Programming

Lecture 11 / Homework 4

Breadth-First Search

- Given source vertex S:
 - Find min. #edges to reach every vertex from S
 - (Assume source is vertex 0)



- Sequential pseudocode:

```
let Q be a queue
Q.enqueue(source)
label source as discovered
source.value <- 0

while Q is not empty
  v ← Q.dequeue()
  for all edges from v to w in G.adjacentEdges(v):
    if w is not labeled as discovered
      Q.enqueue(w)
      label w as discovered, w.value <- v.value + 1
```

Alternate BFS algorithm

- New sequential pseudocode:

Input: V_a , E_a , source (graph in “compact adjacency list” format)

Create frontier (F), visited array (X), cost array (C)

F \leftarrow (all false)

X \leftarrow (all false)

C \leftarrow (all infinity)

F[source] \leftarrow true

C[source] \leftarrow 0

while F is not all false:

Parallelizable!

for $0 \leq i < |V_a|$:

if F[i] is true:

F[i] \leftarrow false

X[i] \leftarrow true

for $E_a[V_a[i]] \leq j < E_a[V_a[i+1]]$:

if X[j] is false:

C[j] \leftarrow C[i] + 1

F[j] \leftarrow true

GPU-accelerated BFS

- CPU-side pseudocode:

```
Input: Va, Ea, source      (graph in "compact adjacency list" format)
Create frontier (F), visited array (X), cost array (C)
F <- (all false)
X <- (all false)
C <- (all infinity)
```

```
F[source] <- true
C[source] <- 0
while F is not all false:
    call GPU kernel( F, X, C, Va, Ea )
```

Can represent boolean values as integers

- GPU-side kernel pseudocode:

```
if F[threadId] is true:

    F[threadId] <- false
    X[threadId] <- true

    for Ea[Va[threadId]] ≤ j < Ea[Va[threadId + 1]]:
        if X[j] is false:
            C[j] <- C[threadId] + 1
            F[j] <- true
```

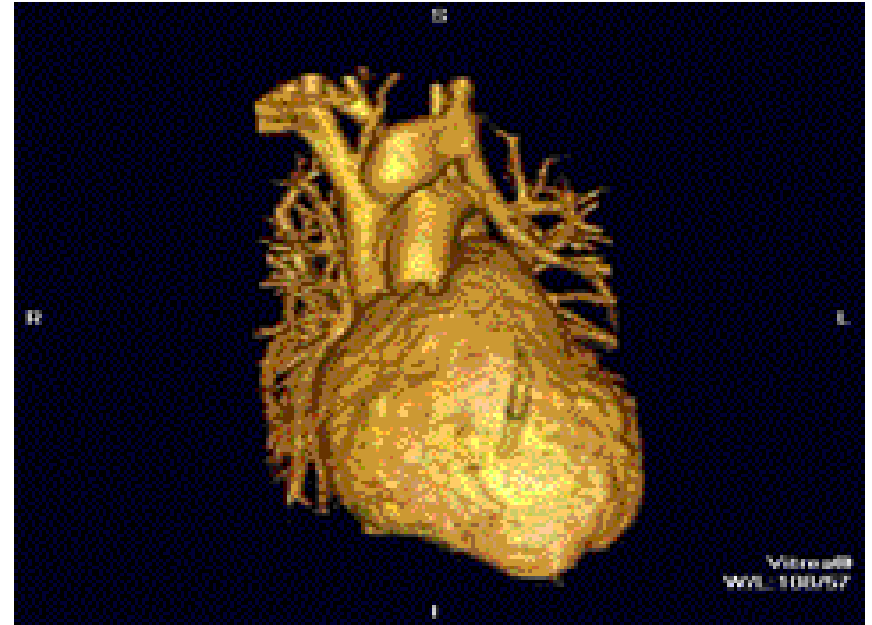
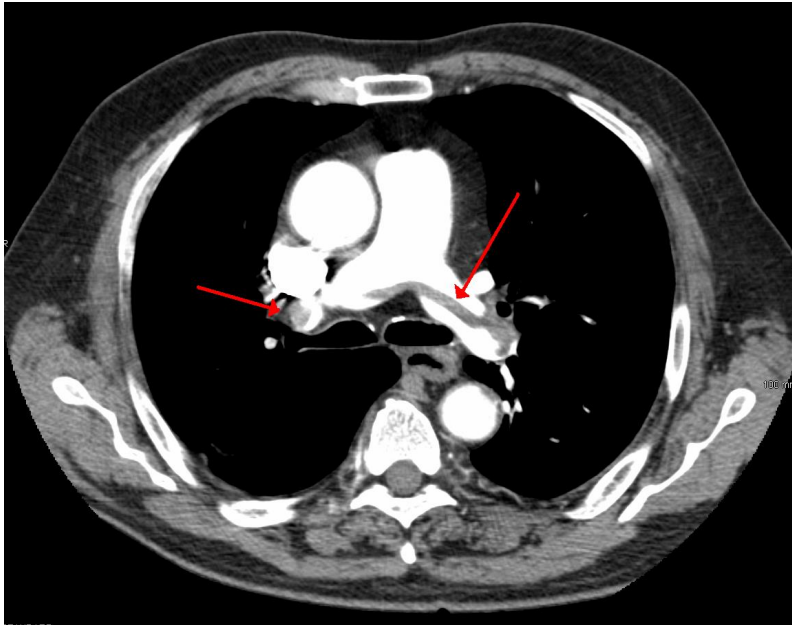
Texture Memory (and co-stars)

- Another type of memory system, featuring:
 - Spatially-cached read-only access
 - Avoid coalescing worries
 - Interpolation
 - (Other) fixed-function capabilities
 - Graphics interoperability

X-ray CT Reconstruction

Medical Imaging

- See inside people!
 - Critically important in medicine today

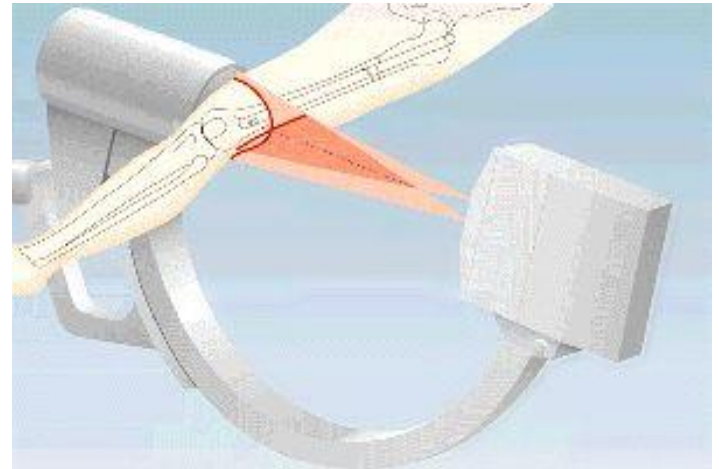


"SaddlePE" by James Heilman, MD - Own work. Licensed under CC BY-SA 3.0 via Wikimedia Commons - <http://commons.wikimedia.org/wiki/File:SaddlePE.PNG#/media/File:SaddlePE.PNG>

"PAPVR". Licensed under CC BY 3.0 via Wikipedia - <http://en.wikipedia.org/wiki/File:PAPVR.gif#/media/File:PAPVR.gif>

X-ray imaging (Radiography)

- “Algorithm”:
 - Generate electromagnetic radiation
 - Measure radiation at the “camera”
- Certain tissues are more “opaque” to X-rays
- Like photography!



"Coude fp" by MB - Collection personnelle. Licensed under CC BY-SA 2.5 via Wikimedia Commons - http://commons.wikimedia.org/wiki/File:Coude_fp.PNG#/media/File:Coude_fp.PNG

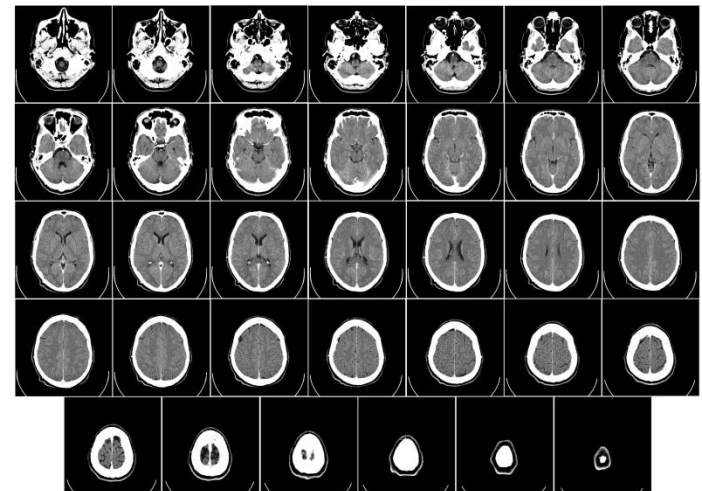
<http://www.imaginis.com/xray/how-does-x-ray-imaginig-work>

Radiography limitations

- Generates 2D image of 3D body
- What if we want a “slice” of 3D body?
 - Goal: 3D reconstruction!
(from multiple slices)



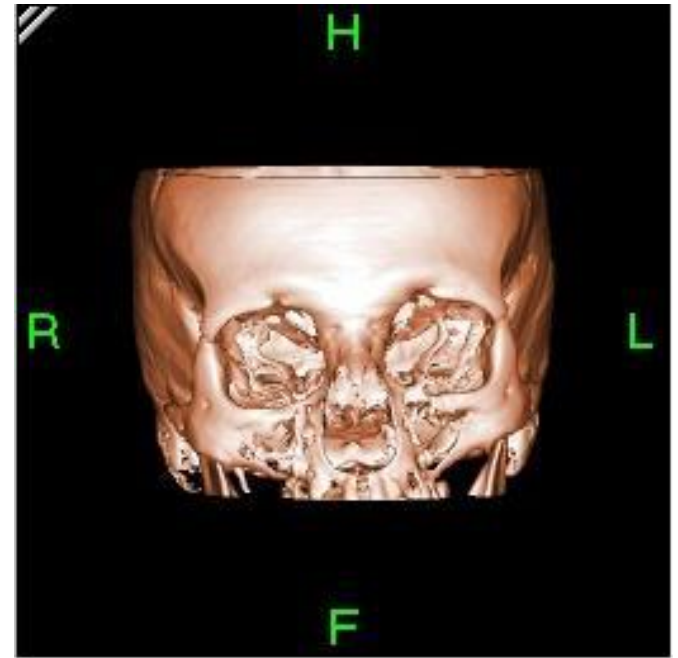
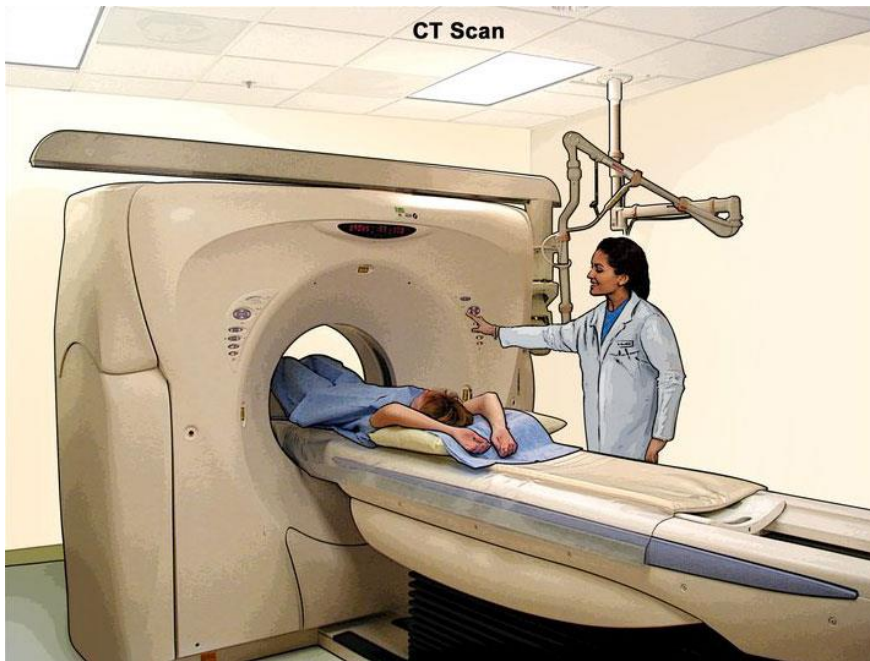
vs.



"Coude fp" by MB - Collection personnelle. Licensed under CC BY-SA 2.5 via Wikimedia Commons - http://commons.wikimedia.org/wiki/File:Coude_fp.PNG#/media/File:Coude_fp.PNG

"Computed tomography of human brain - large" by Department of Radiology, Uppsala University Hospital. Uploaded by Mikael Häggström. - Radiology, Uppsala University Hospital. Brain supplied by Mikael Häggström. It was taken Mars 23, 2007. Licensed under CC0 via Wikimedia Commons - http://commons.wikimedia.org/wiki/File:Computed_tomography_of_human_brain_-_large.png#/media/File:Computed_tomography_of_human_brain_-_large.png

X-ray Computed Tomography (CT)

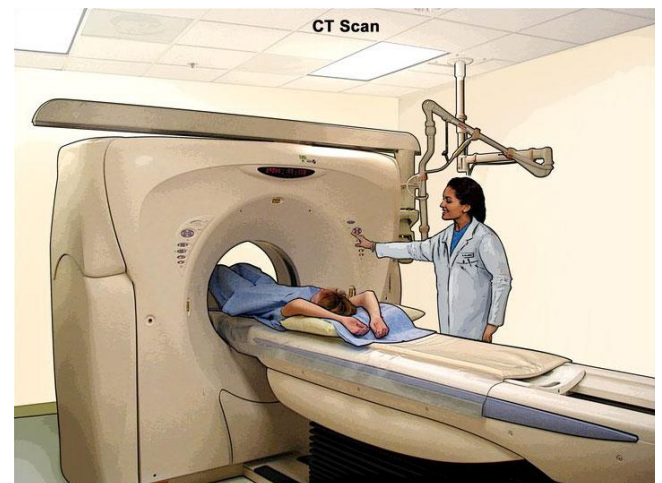
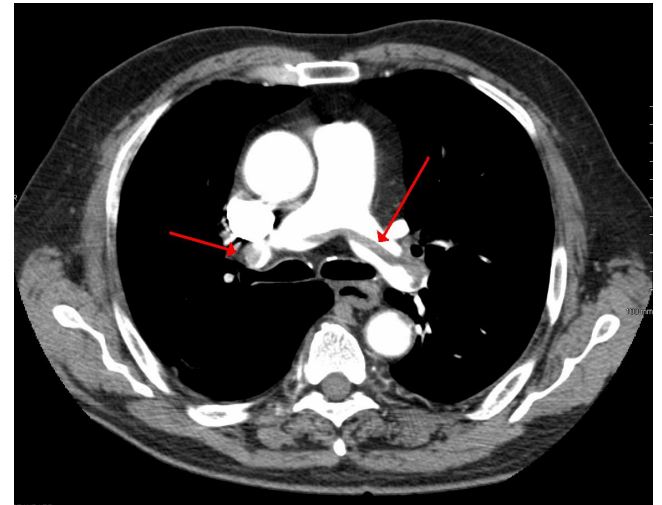


<http://www.cancer.gov/>

"Bonereconstruction" by Original uploader was Zgyorfi at en.wikipedia - Transferred from en.wikipedia; transferred to Commons by User:Common Good using CommonsHelper.. Licensed under CC BY-SA 3.0 via Wikimedia Commons - <http://commons.wikimedia.org/wiki/File:Bonereconstruction.jpg#/media/File:Bonereconstruction.jpg>

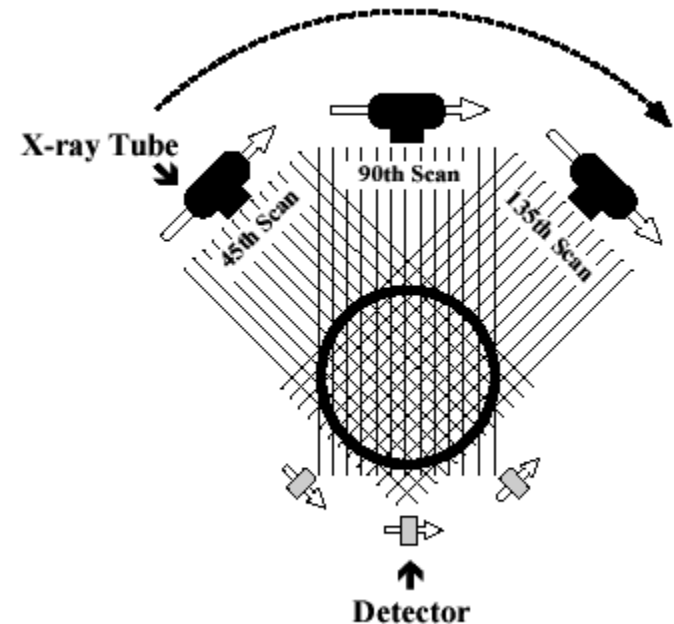
X-ray Computed Tomography (CT)

- Generate 2D “slice” using 3D imaging
 - New imaging possibilities!
- Reconstruction less straightforward



X-ray Computed Tomography (CT)

- “Algorithm” (per-slice):
 - Take *lots* of pictures at different angles
 - Each “picture” is a 1-D line
 - Reconstruct the many 1-D pictures into a 2-D image
- Harder, more computationally intensive!
 - 3D reconstruction requires multiple slices



Mathematical Details

- X-ray CT (per-slice) performs a 2D *X-ray transform* (eq. to 2D *Radon transform*):
 - Suppose body density represented by $f(\vec{x})$ within 2D slice, $\vec{x} = (x, y)$
 - Assume linear attenuation of radiation
 - For each line L of radiation measured by detector:

$$I_{detect} = I_{emit} \int_L f = I_{emit} \int_{\mathbb{R}} f(\vec{x}_0 + t\vec{\theta}_L) dt$$

- $\vec{\theta}_L$: a unit vector in direction of L

Mathematical Details

$$I_{detect} = I_{emit} \int_L f = I_{emit} \int_{\mathbb{R}} f(\vec{x}_0 + t\vec{\theta}_L) dt$$

- Defined as Lebesgue integral – non-oriented
 - Opposite radiation direction should have same attenuation!
 - Re-define as:

$$I_{detect} = I_{emit} \int_{-\infty}^{\infty} f(\vec{x}_0 + t\vec{\theta}_L) |dt|$$

Mathematical Details

- For each line L of radiation measured by detector:

$$I_{detect} = I_{emit} \int_L f = I_{emit} \int_{-\infty}^{\infty} f(\vec{x}_0 + t\vec{\theta}_L) |dt|$$

- Define general X-ray transform (for all lines L in \mathbb{R}^2):

$$(Rf)(L) = \int_{-\infty}^{\infty} f(\vec{x}_0 + t\vec{\theta}_L) |dt|$$

- Fractional values of attenuation
- \vec{x}_0 lies along L

Mathematical Details

- Define general X-ray transform:

$$(Rf)(L) = \int_{-\infty}^{\infty} f(\vec{x}_0 + t\vec{\theta}_L) |dt|$$

- Parameterize $\vec{\theta} = (\cos \theta, \sin \theta)$

- Redefine as:

$$(Rf)(\vec{x}_0, \theta) = \int_{-\infty}^{\infty} f(\vec{x}_0 + t\vec{\theta}) |dt|$$

- Define for $\theta \in [0, 2\pi)$

Mathematical Details

$$(Rf)(\vec{x}_0, \theta) = \int_{-\infty}^{\infty} f(\vec{x}_0 + t\vec{\theta}) |dt|$$

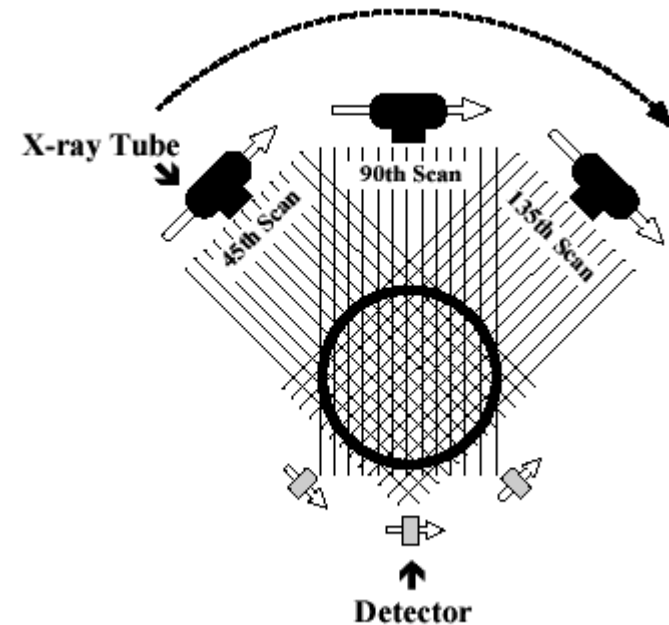
- Important properties:
 - Many \vec{x}_0 are redundant!
 - Symmetry: $Rf(\vec{x}_0, \theta) = Rf(\vec{x}_0, \theta + \pi)$
 - Can define for $\theta \in [0, \pi)$

X-ray Computed Tomography (CT)

- Redefined X-ray transform, $\theta \in [0, \pi)$:

$$(Rf)(\vec{x}_0, \theta) = \int_{-\infty}^{\infty} f(\vec{x}_0 + t\vec{\theta}) |dt|$$

- In reality:
 - Only defined for some θ !



X-ray CT *Reconstruction*

- Given the results of our scan (the *sinogram*):

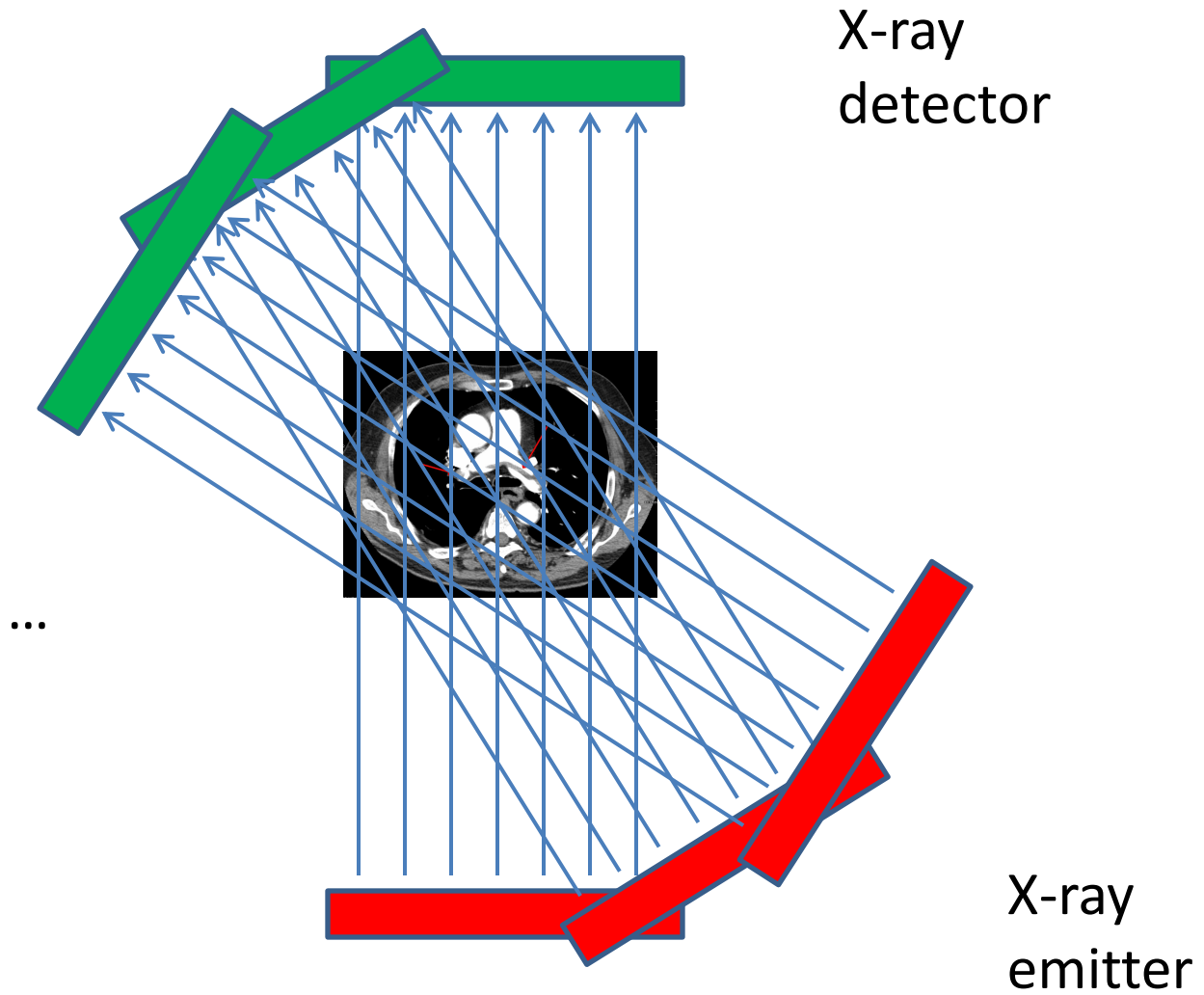
$$(Rf)(\vec{x}_0, \theta) = \int_{-\infty}^{\infty} f(\vec{x}_0 + t\vec{\theta}) |dt|$$

- Obtain the original data: (“*density*” of our body)

$$f(x, y)$$

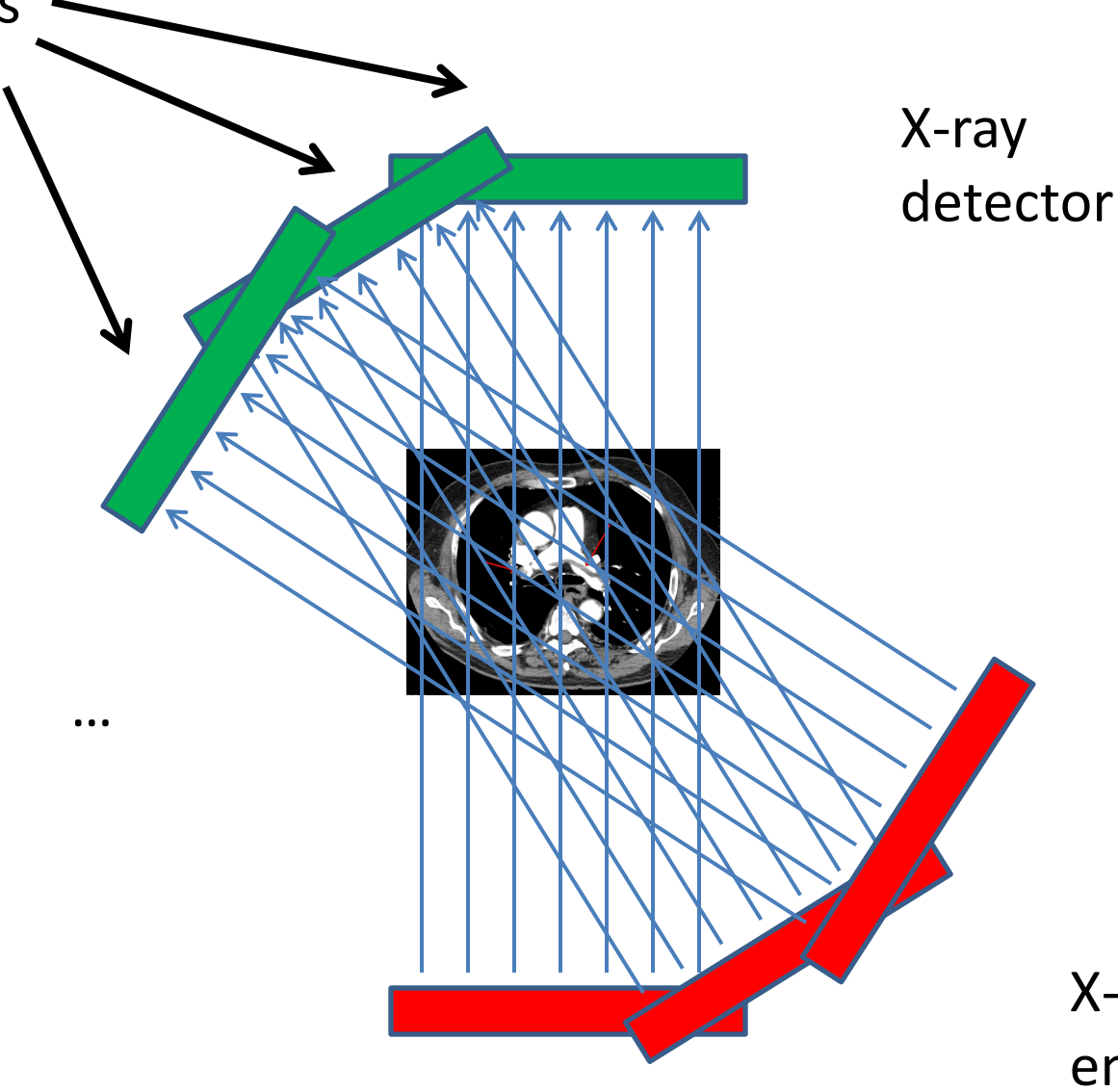
- In reality:
 - This is hard
 - We only scanned at certain (discrete) values of θ !
 - Consequence: Perfect reconstruction is impossible!

Reconstruction



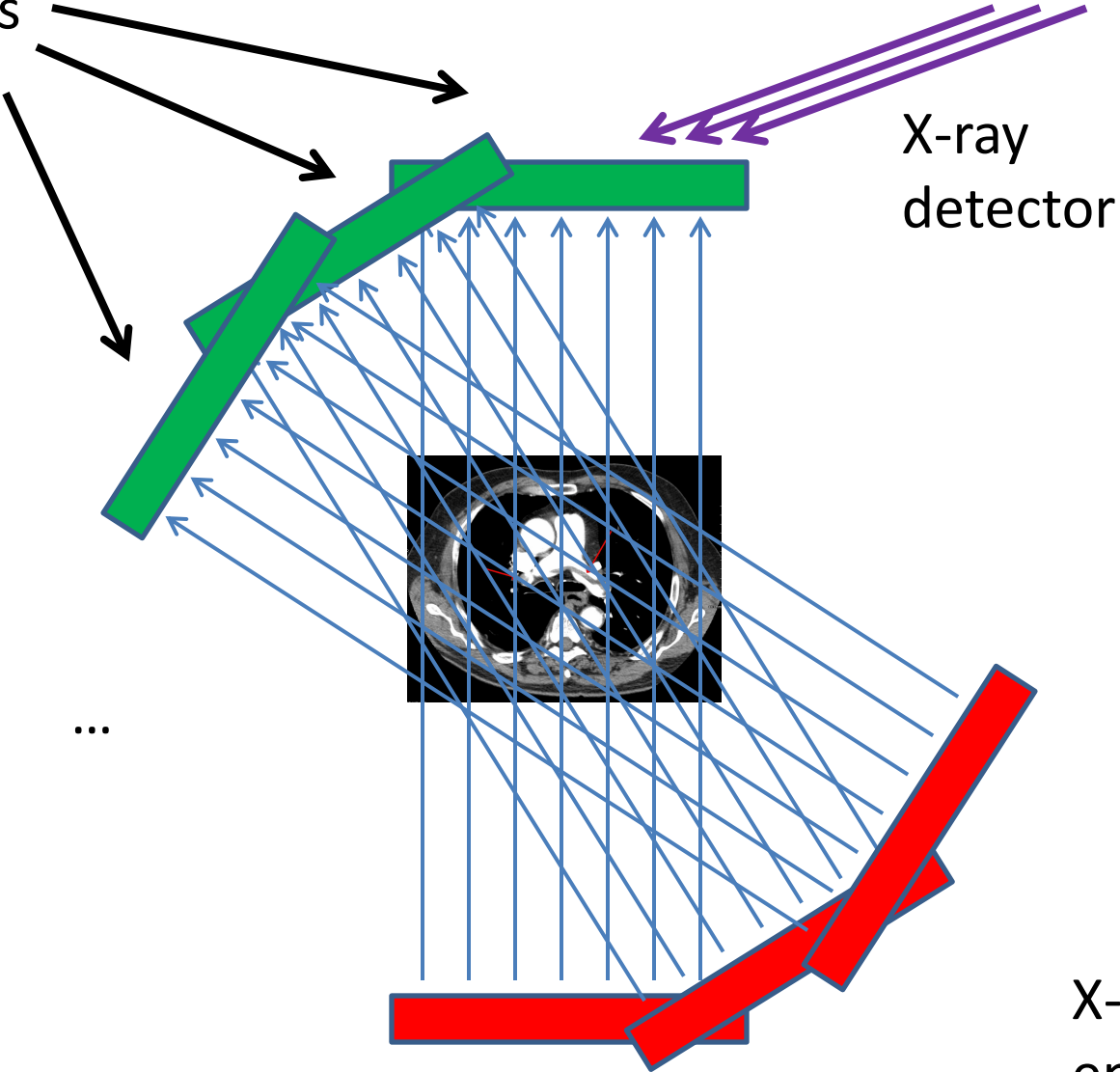
Reconstruction

Different θ 's



Reconstruction

Different θ 's



Each location on detector:
Corresponds to multiple x_0 's

X-ray detector

X-ray emitter

X-ray CT *Reconstruction*

- Given the results of our scan (the *sinogram*):

$$(Rf)(\vec{x}_0, \theta) = \int_{-\infty}^{\infty} f(\vec{x}_0 + t\vec{\theta}) |dt|$$

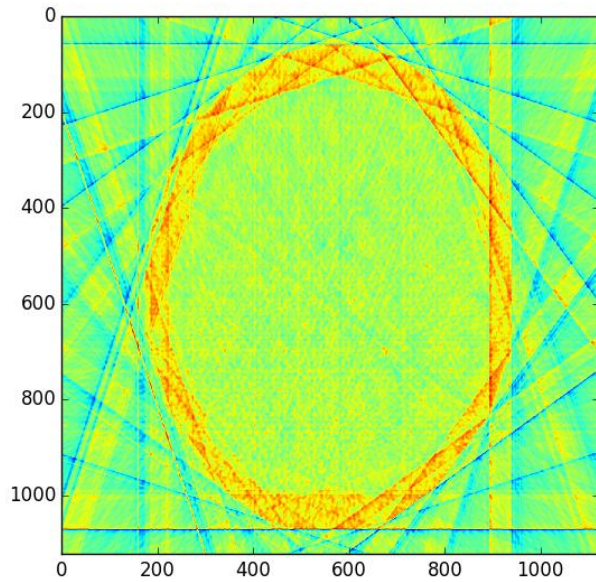
- Obtain the original data: (“*density*” of our body)

$$f(x, y)$$

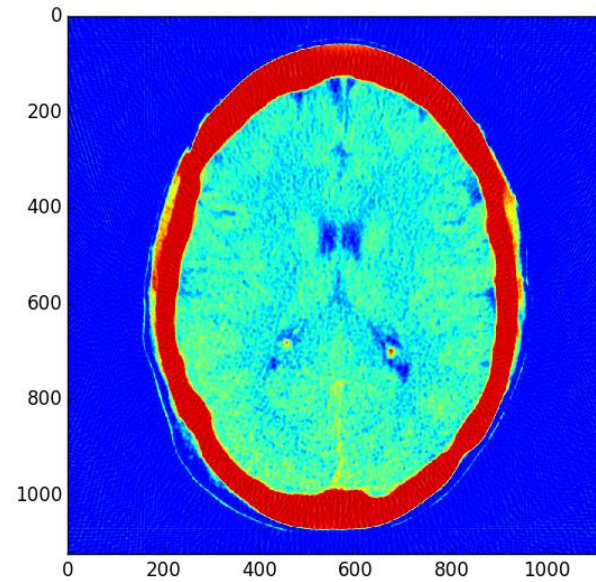
- In reality:
 - This is hard
 - We only scanned at certain (discrete) values of θ !
 - Consequence: Perfect reconstruction is impossible!

Imperfect Reconstruction

10 angles of imaging



200 angles of imaging



Reconstruction

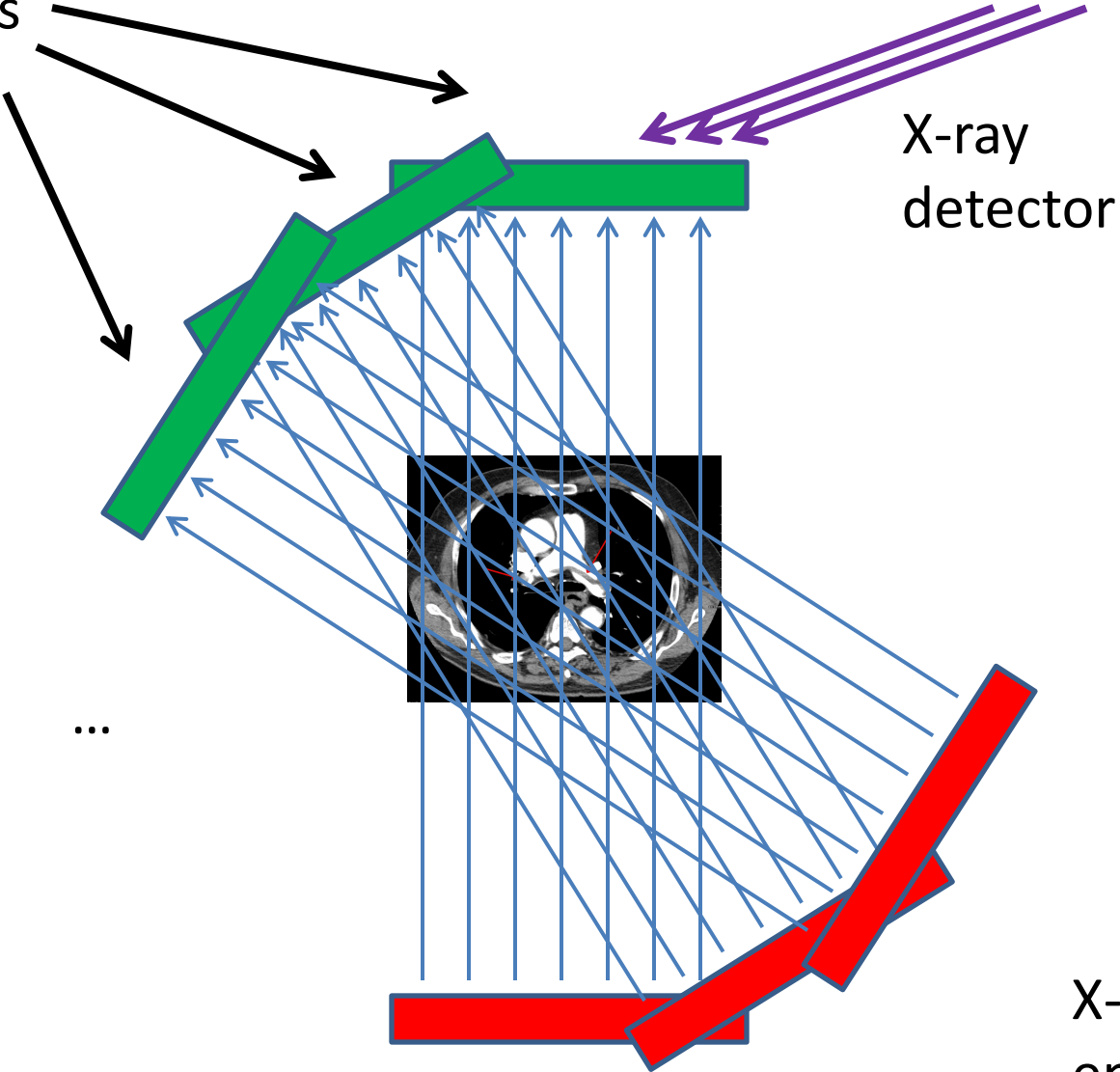
- Simpler algorithm – backprojection
 - Not quite inverse Radon transform!
- Claim: Can reconstruct image as:

$$f_r(\vec{x}) = \sum_{\theta} (Rf)(\vec{x}, \theta) = \sum_{\theta} \int_{-\infty}^{\infty} f(\vec{x} + t\vec{\theta}) |dt|$$

- (θ 's where X-rays are taken)
- In other words: To reconstruct point, sum measurement along *every line passing through that point*

Reconstruction

Different θ 's



Each location on detector:
Corresponds to multiple x_0 's

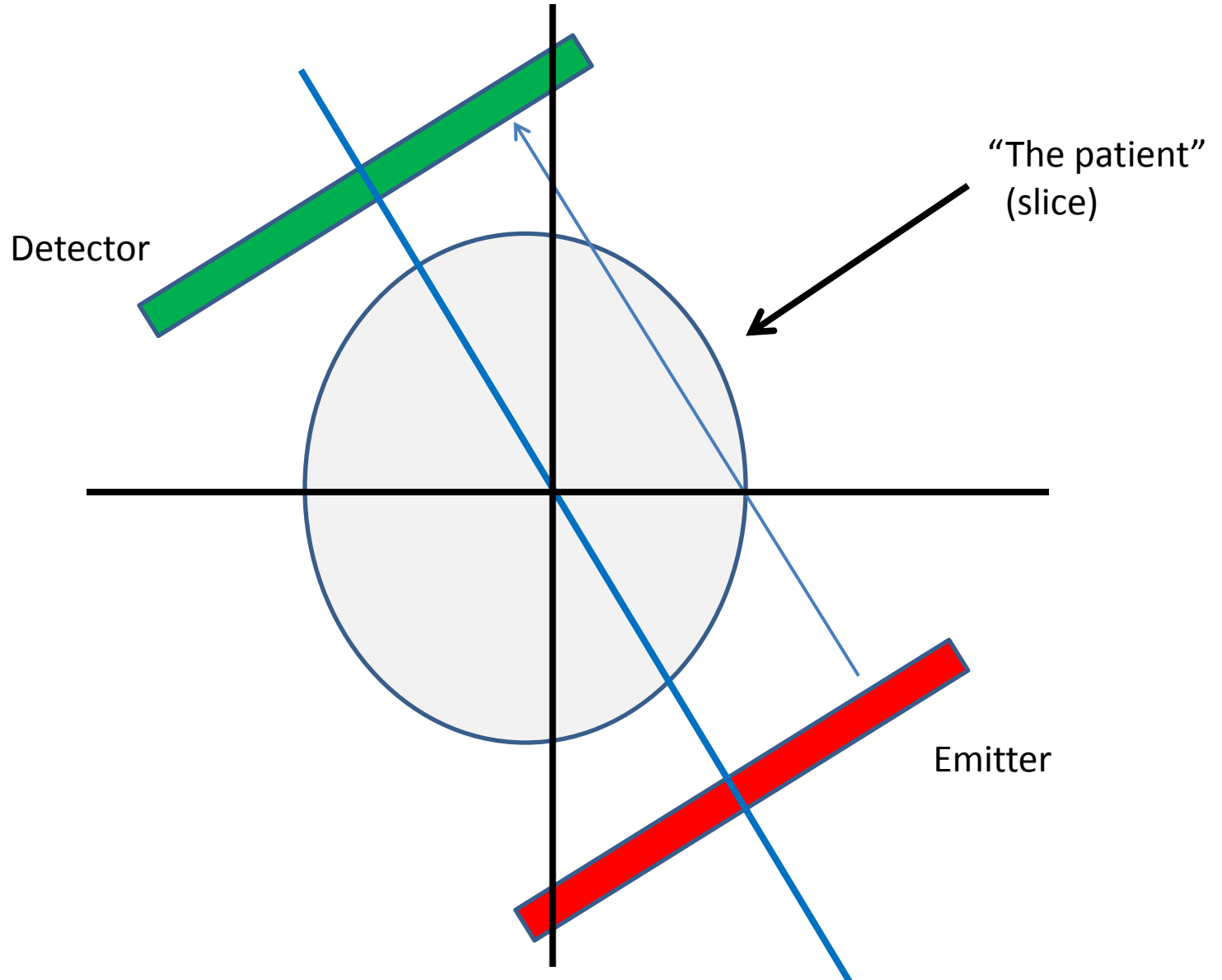
X-ray detector

X-ray emitter

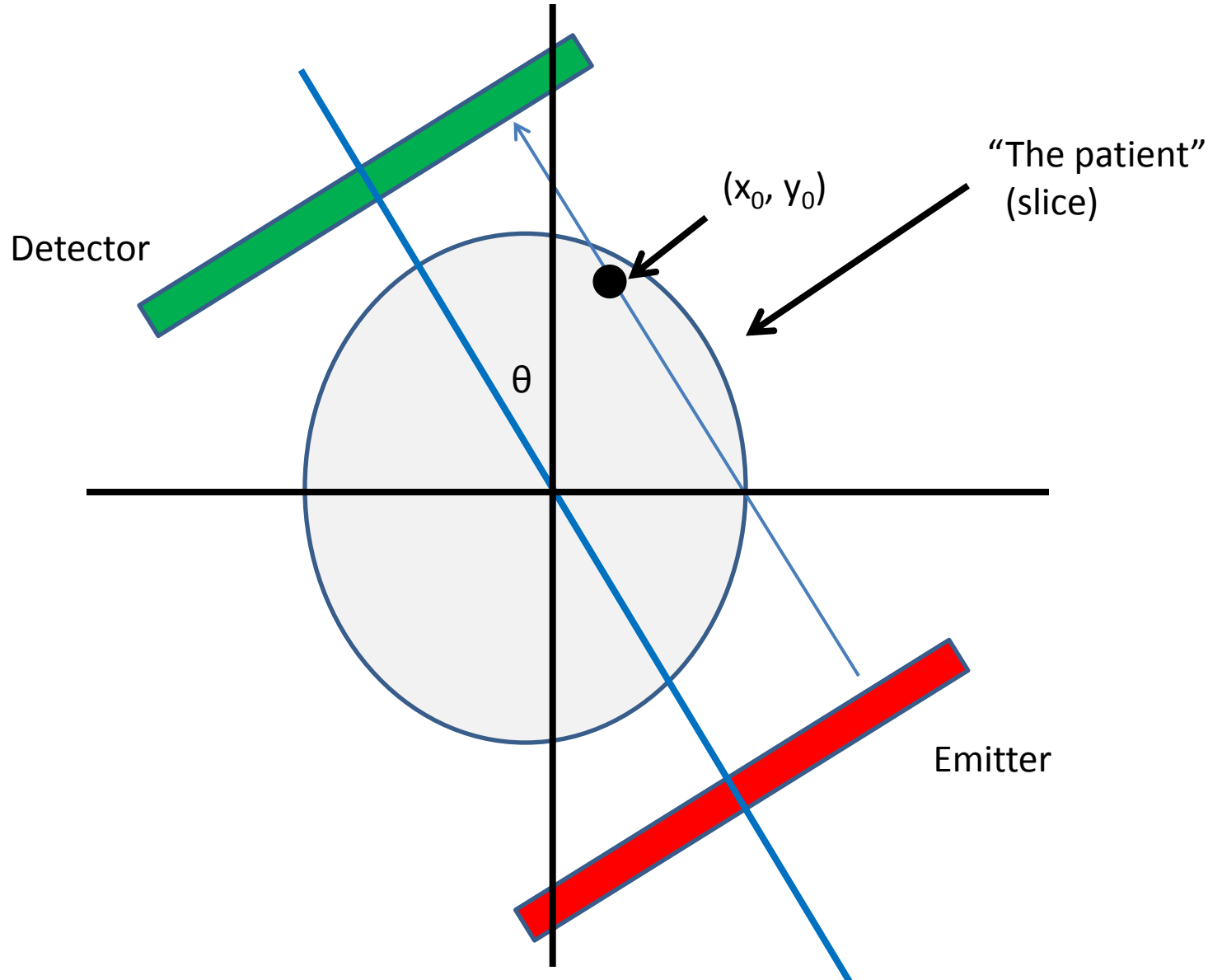
Geometry Details

- For x_0 , need to find:
 - At each θ , which radiation measurement corresponds to the line passing through x_0 ?

Geometry Details

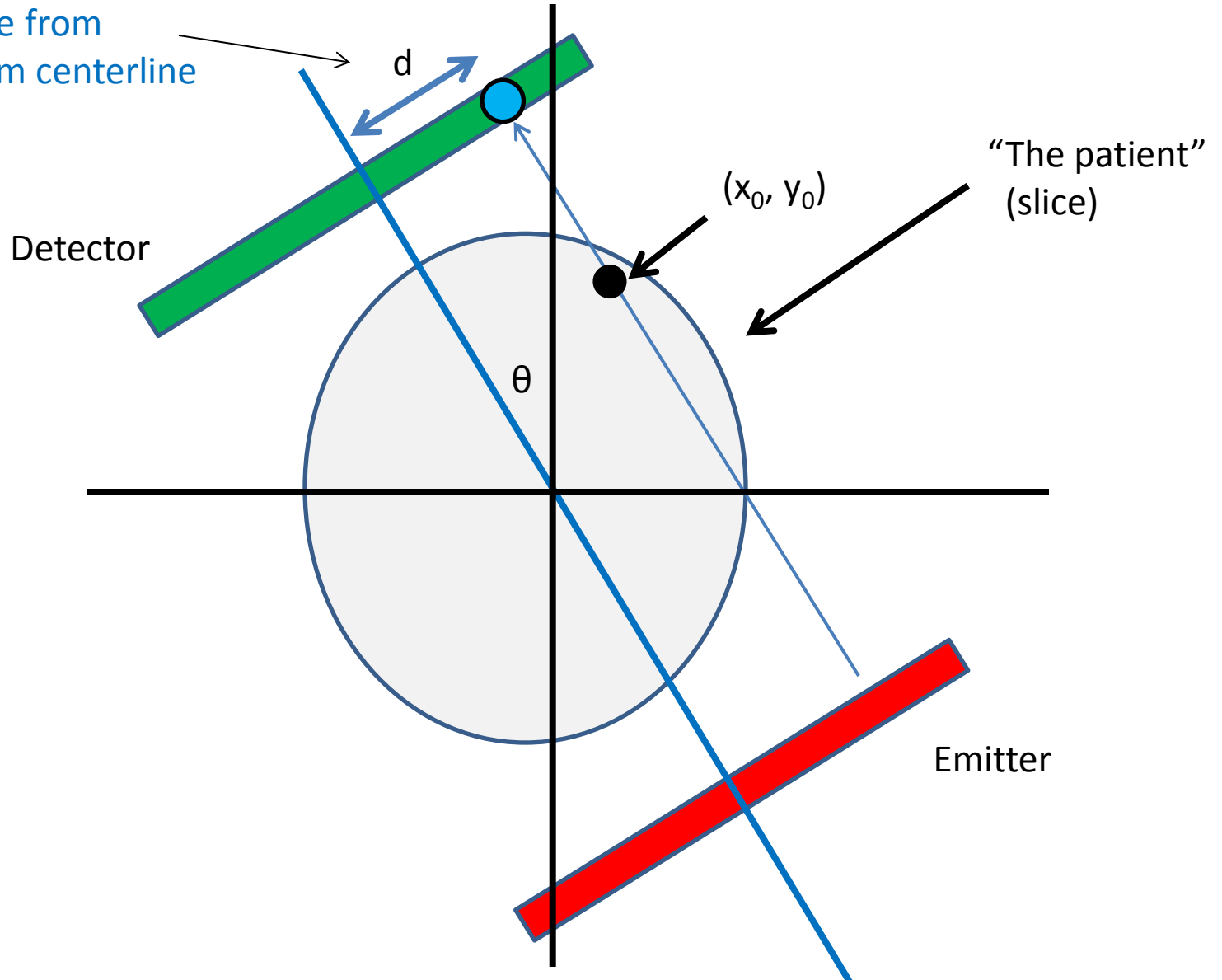


Geometry Details



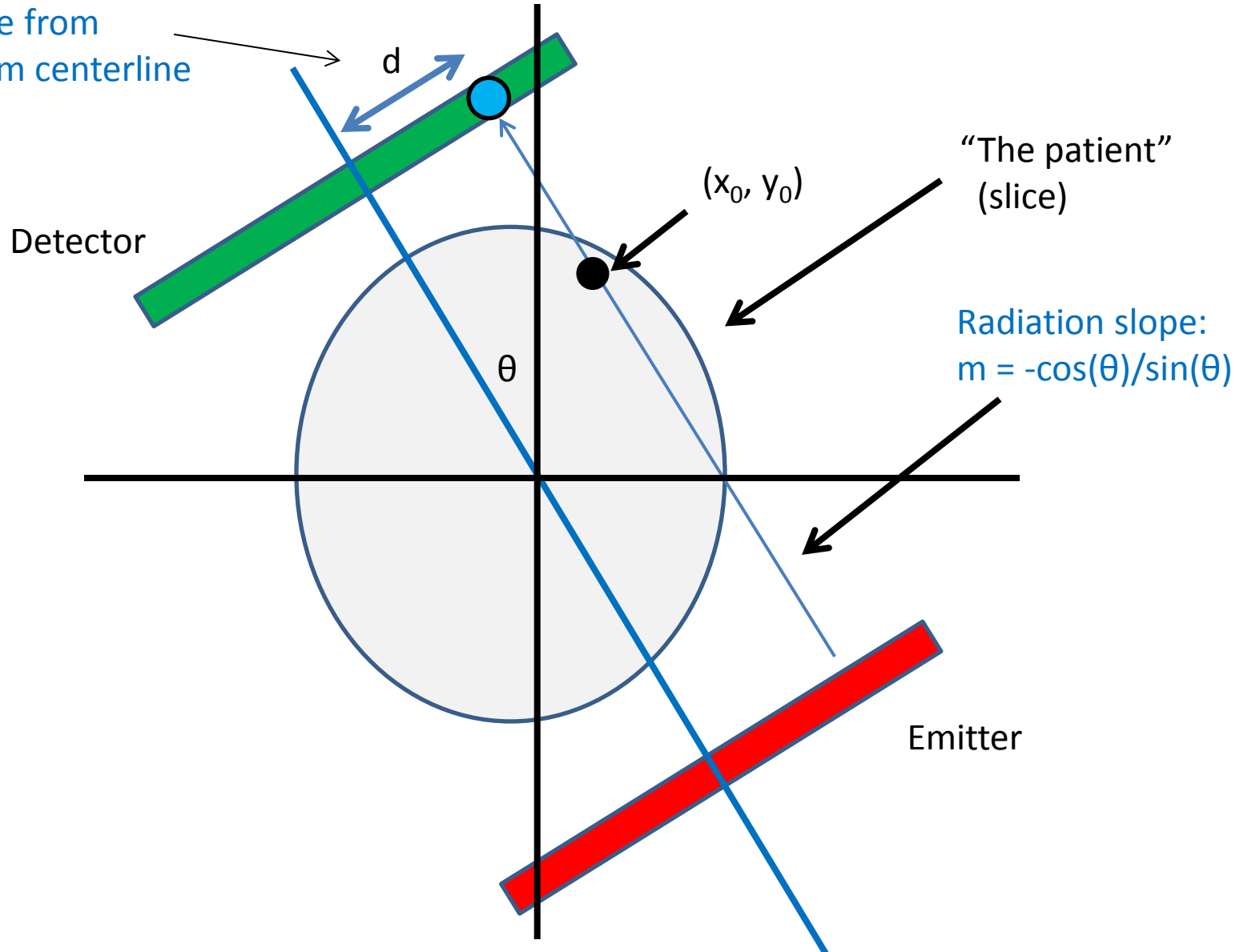
Geometry Details

Distance from
sinogram centerline



Geometry Details

Distance from
sinogram centerline



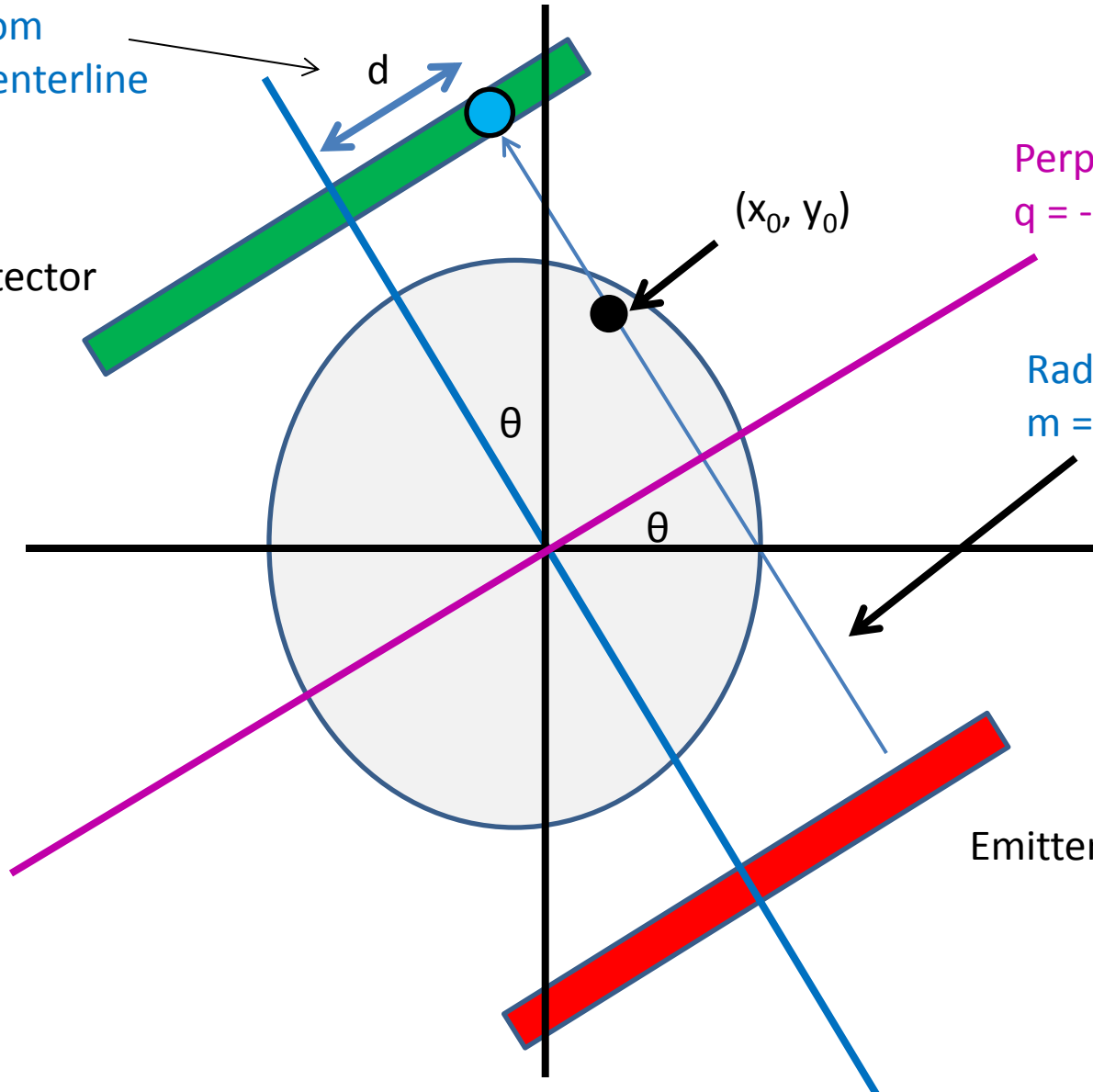
Geometry Details

Distance from
sinogram centerline

Detector

Perpendicular slope:
 $q = -1/m$ (correction)

Radiation slope:
 $m = -\cos(\theta)/\sin(\theta)$



d

(x_0, y_0)

θ

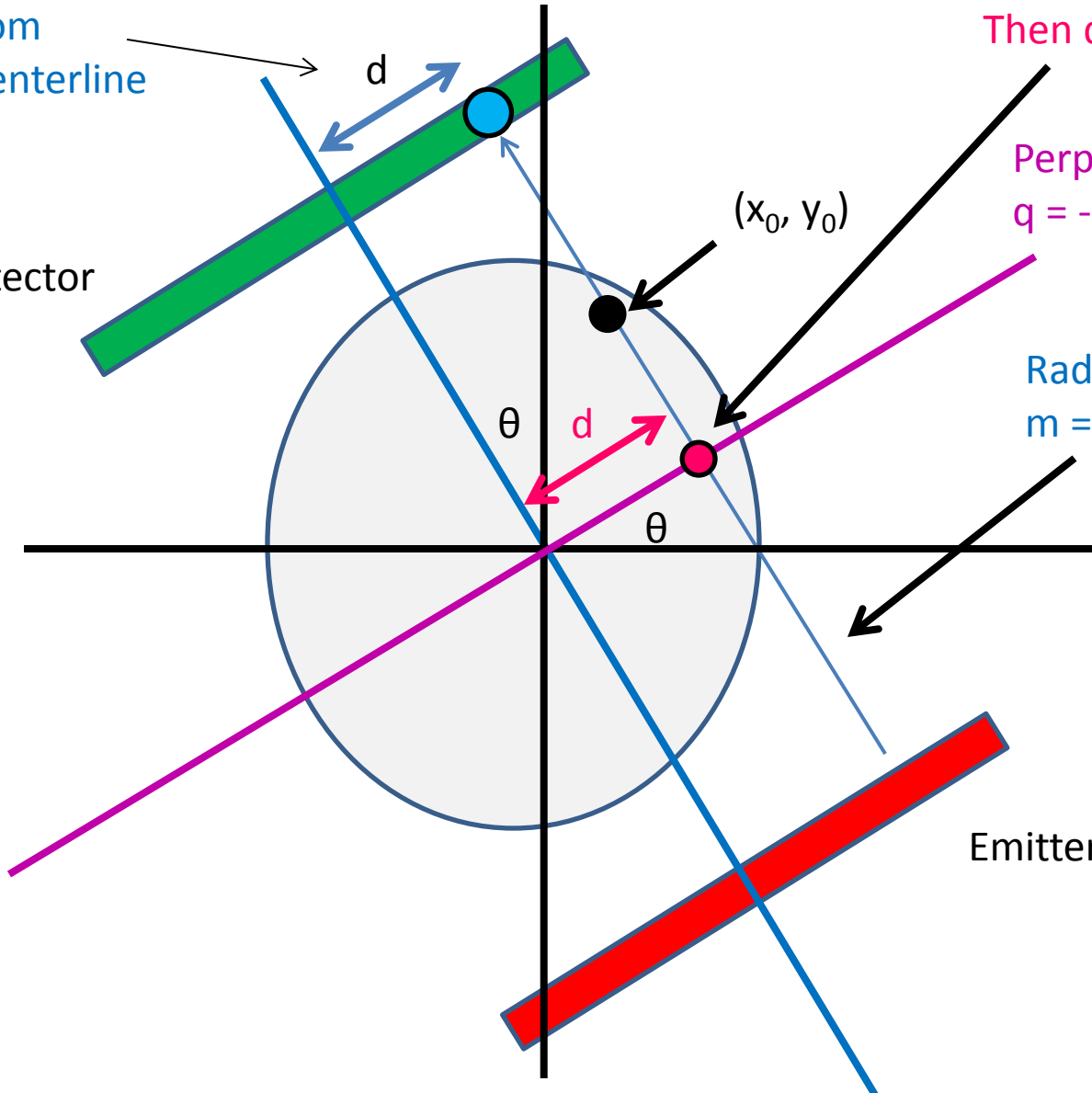
θ

Emitter

Geometry Details

Distance from
sinogram centerline

Detector



Find intersection
point (x_i, y_i)
Then $d^2 = x_i^2 + y_i^2$

Perpendicular slope:
 $q = -1/m$ (correction)

Radiation slope:
 $m = -\cos(\theta)/\sin(\theta)$

Emitter

Intersection point

- Line 1: (point-slope)

$$(y_i - y_0) = m(x_i - x_0)$$

- Line 2:

$$y_i = qx_i$$

Corrections

- Combine and solve:

$$x_i = \frac{y_0 - mx_0}{q - m}, y_i = qx_i$$

Intersection point

- Intersection point:

$$x_i = \frac{y_0 - m x_0}{q - m}, \quad y_i = q x_i$$

Corrections

- Distance from measurement centerline:

$$d = \sqrt{x_i^2 + y_i^2}$$

Geometry Details

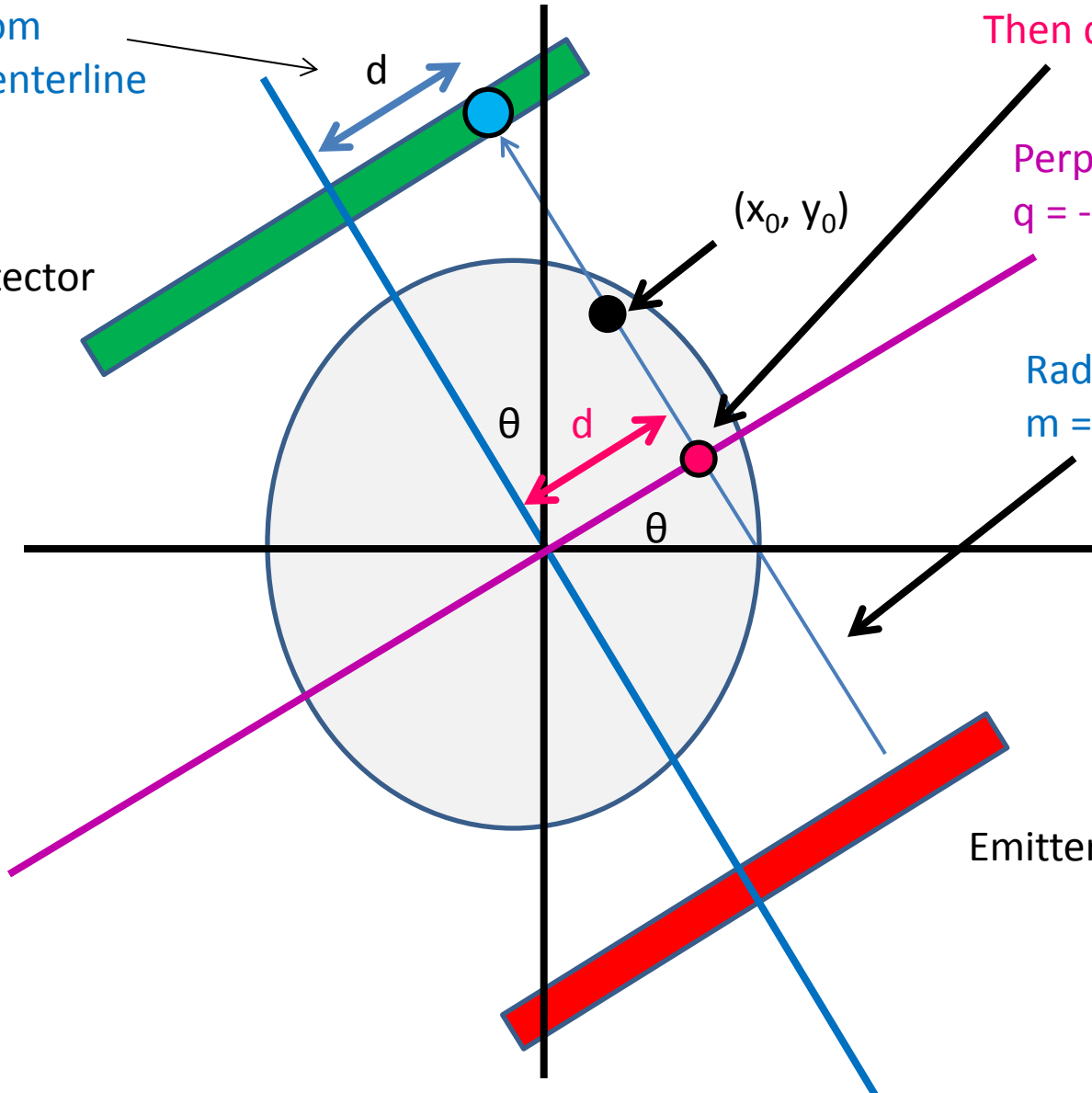
Distance from
sinogram centerline

Detector

Find intersection
point (x_i, y_i)
Then $d^2 = x_i^2 + y_i^2$

Perpendicular slope:
 $q = -1/m$ (correction)

Radiation slope:
 $m = -\cos(\theta)/\sin(\theta)$



Emitter

Sequential pseudocode

(input: X-ray sinogram):
(allocate output image)

$$f_r(\vec{x}) = \sum_{\theta} (Rf)(\vec{x}, \theta)$$

```
for all y in image:  
  for all x in image:  
    for all theta in sinogram:
```

Clarification: Remember not
to confuse geometric x,y
with pixel x,y!

```
      calculate m from theta  
      calculate x_i, y_i from m, -1/m  
      calculate d from x_i, y_i  
      image[x,y] += sinogram[theta, "distance"]
```

(0,0) geometrically is the
center pixel of the image,
and (0,0) in pixel coordinates
is the upper left hand corner.
Image is indexed row-wise

Correction/clarification:

- d is the distance from the center of the sinogram – remember to center index appropriately
- Use $-d$ instead of d as appropriate (when $-1/m > 0$ and $x_i < 0$, or if $-1/m < 0$ and $x_i > 0$)

Sequential pseudocode

(input: X-ray sinogram):
(allocate output image)

$$f_r(\vec{x}) = \sum_{\theta} (Rf)(\vec{x}, \theta)$$

```
for all y in image:  
  for all x in image:  
    for all theta in sinogram:  
      calculate m from theta  
      calculate x_i, y_i from m, -1/m  
      calculate d from x_i, y_i  
      image[x,y] += sinogram[theta, "distance"]
```

Parallelizable!
Inside loop depends
only on x, y, theta

(corrections/clarification –
see slide 37)

Sequential pseudocode

(input: X-ray sinogram):
(allocate output image)

$$f_r(\vec{x}) = \sum_{\theta} (Rf)(\vec{x}, \theta)$$

for all y in image:
 for all x in image:

 for all theta in sinogram:

 calculate m from theta

 calculate x_i, y_i from m, $-1/m$

 calculate d from x_i, y_i

 image[x,y] += sinogram[theta, "distance"]

For this assignment, only
parallelize w/r/to x, y

(provides lots of
parallelization already,
other issues)

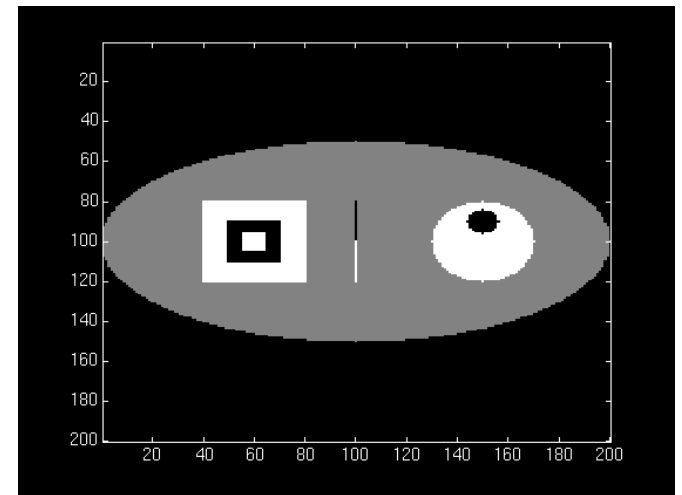
(corrections/clarification –
see slide 37)

Cautionary notes

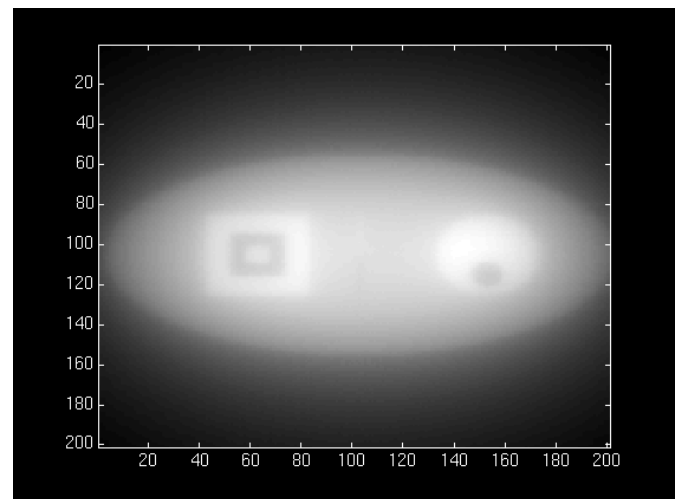
- y in an image is opposite of y geometrically!
 - (Graphics/computing convention)
- Edge cases (divide-by-0):
 - $\theta = 0$:
 - $d = x_0$
 - $\theta = \pi/2$:
 - $d = y_0$

Almost a good reconstruction!

Original

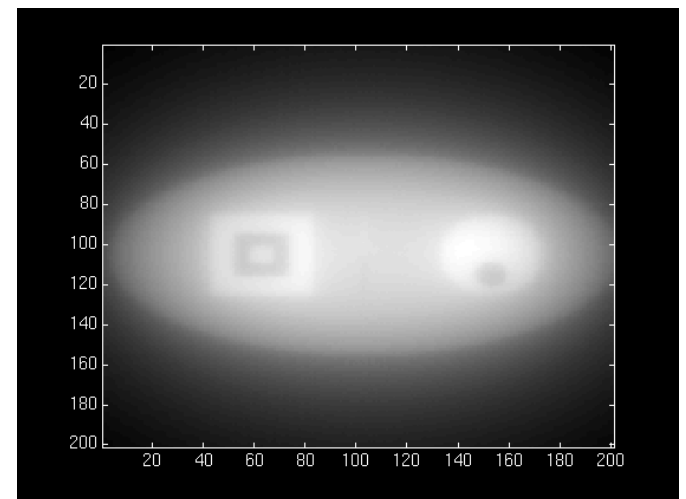
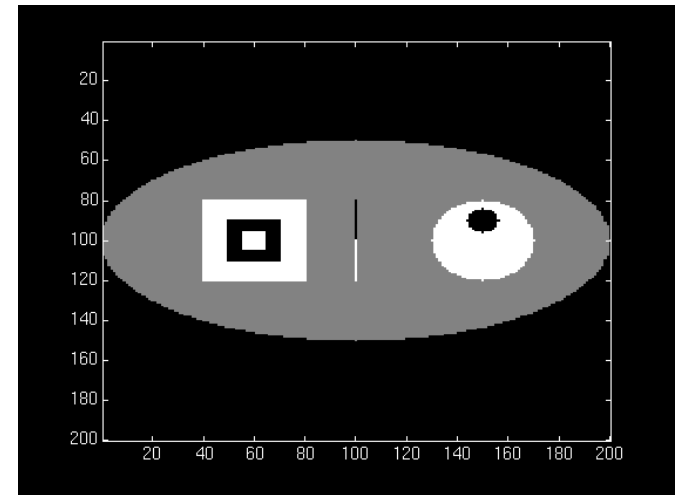


Reconstruction



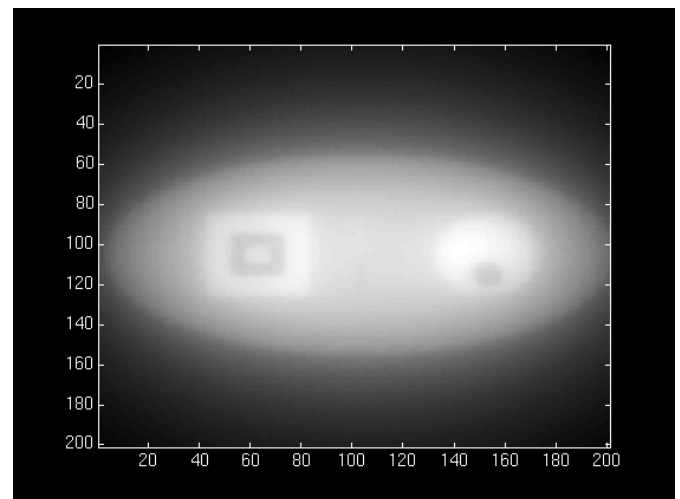
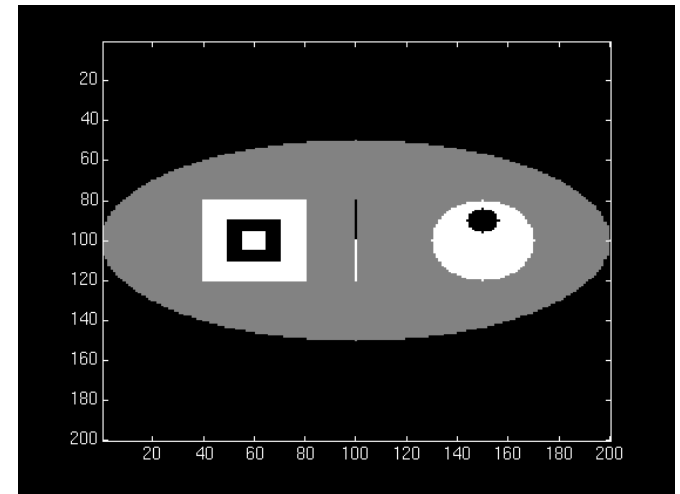
Almost a good reconstruction!

- “Backprojection blur”
 - Similar to low-pass property of SMA (Week 1)
 - We need an “anti-blur”! (opposite of Homework 1)



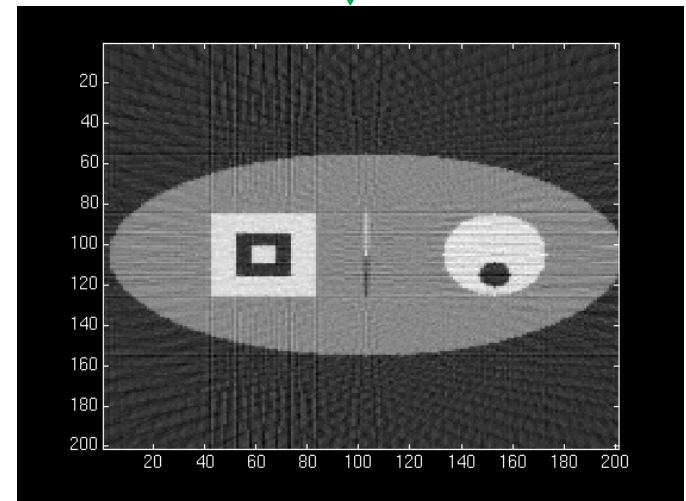
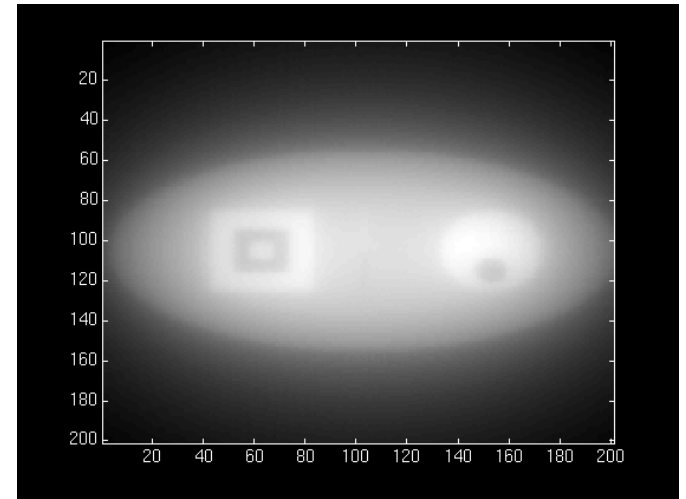
Almost a good reconstruction!

- Solution:
 - A “high-pass filter”
 - We can get frequency info in parallelizable manner!
 - (FFT, Week 3)



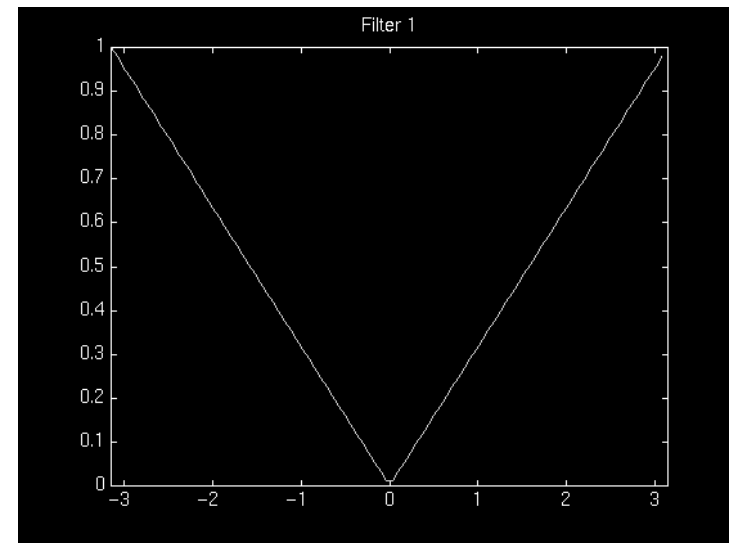
Almost a good reconstruction!

- Solution:
 - A “high-pass filter”
 - We can get frequency info in parallelizable manner!
 - (FFT, Week 3)



High-pass filtering

- Instead of filtering on image (2D HPF):
 - Filter on sinogram! (1D HPF)
 - (Equivalent reconstruction by linearity)
 - Use cuFFT batch feature!
- We'll use a “ramp filter”
 - Retained amplitude is linear function of frequency



Almost a good reconstruction!

- CPU-side:

(input: X-ray sinogram):

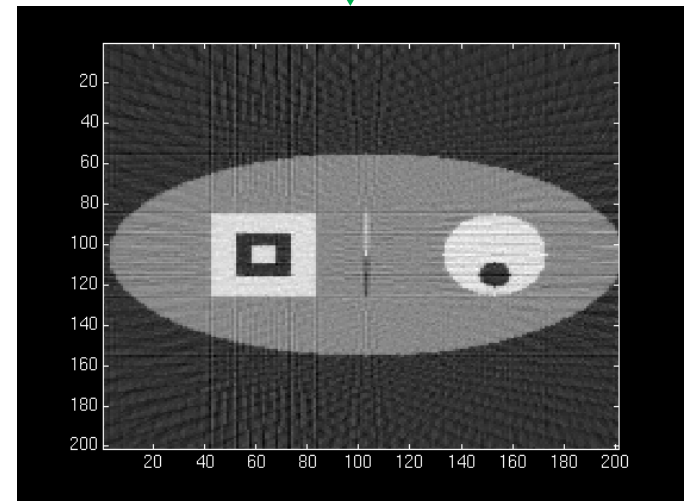
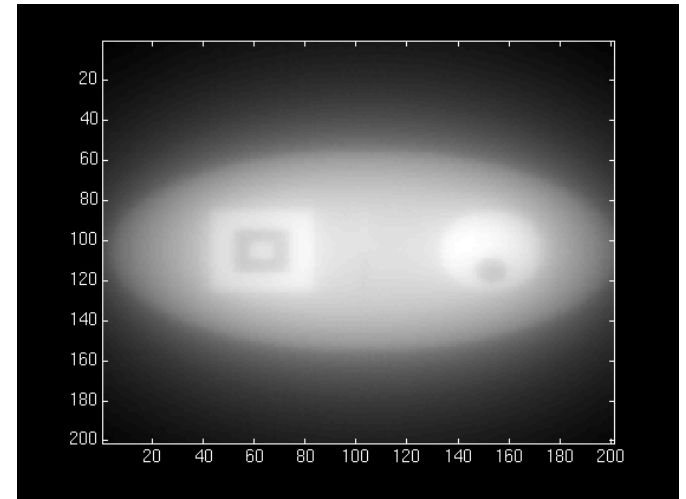
```
calculate FFT on sinogram using cuFFT
call filterKernel on freq-domain data
calculate IFFT on freq-domain data
-> get new sinogram
```

- GPU-side:

filterKernel:

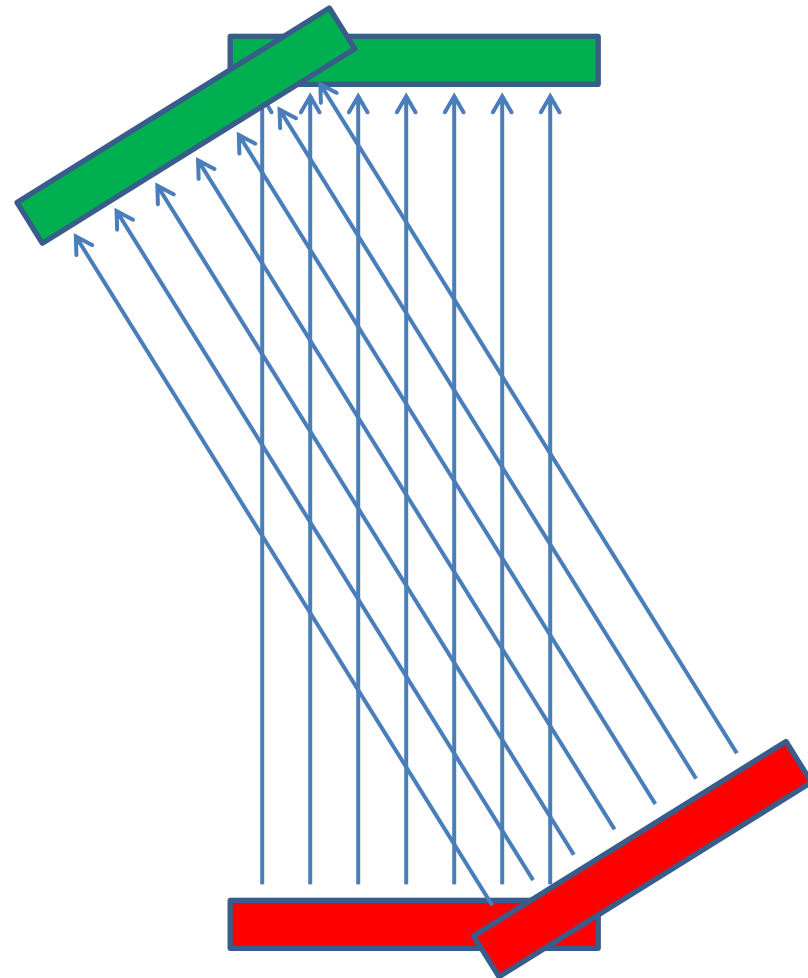
Select specific freq-amplitude
based on thread ID

Get new amplitude from
ramp equation



GPU Hardware

- Non-coalesced access!
 - Sinogram 0, index $\sim d_0$
 - Sinogram 1, index $\sim d_1$
 - Sinogram 2, index $\sim d_2$
 - ...



GPU Hardware

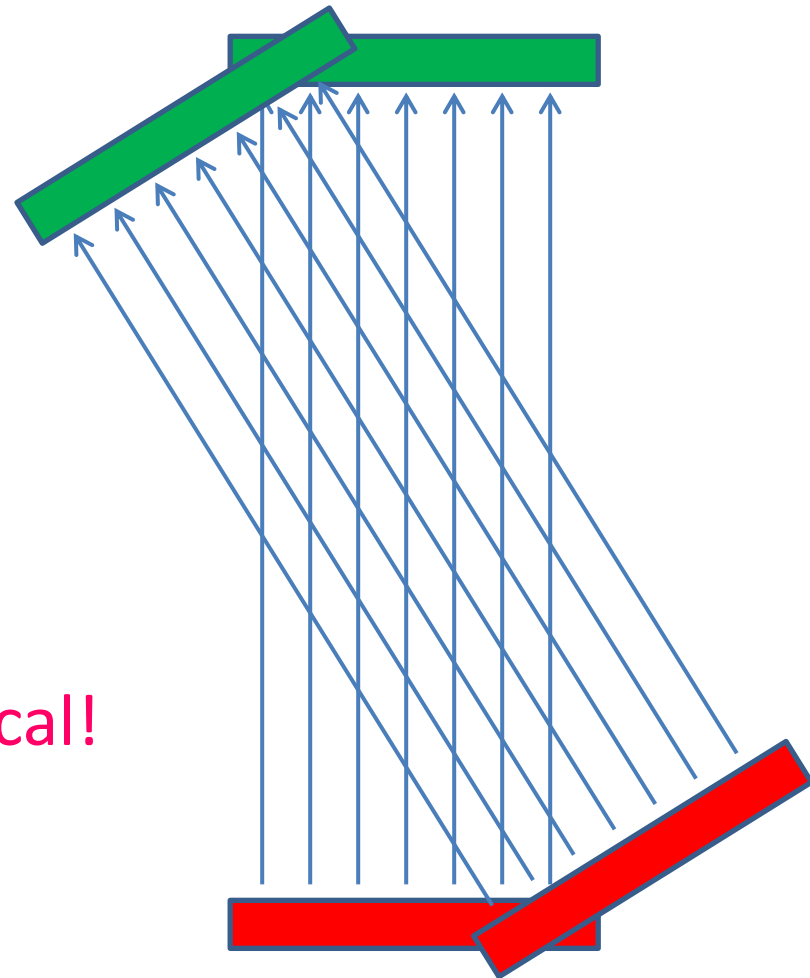
- Non-coalesced access!
 - Sinogram 0, index $\sim d_0$
 - Sinogram 1, index $\sim d_1$
 - Sinogram 2, index $\sim d_2$
 - ...

- However:

- Accesses are 2D spatially local!

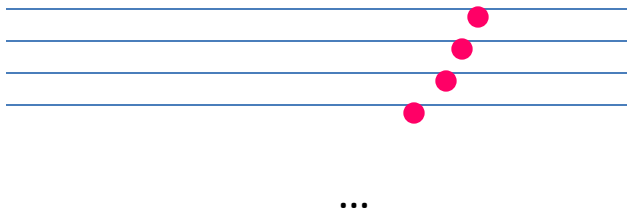


...



GPU Hardware

- Solution:
 - Cache sinogram in texture memory!
 - Read-only (un-modified once we load it)
 - Ignore coalescing
 - 2D spatial caching!



Summary/pseudocode

(input: X-ray sinogram)

Filter sinogram (Slide 46)

Set up 2D texture cache on sinogram (Lecture 10):

- Copy to CUDA array (2D)

- Set addressing mode (clamp)

- Set filter mode (linear, but won't matter)

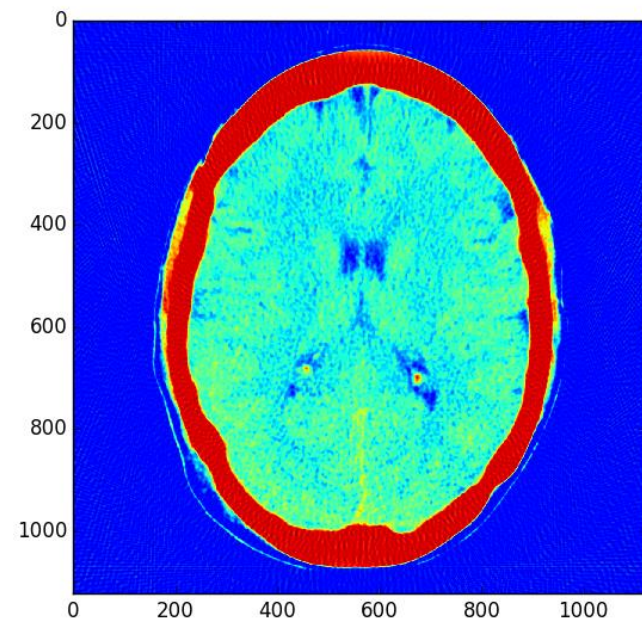
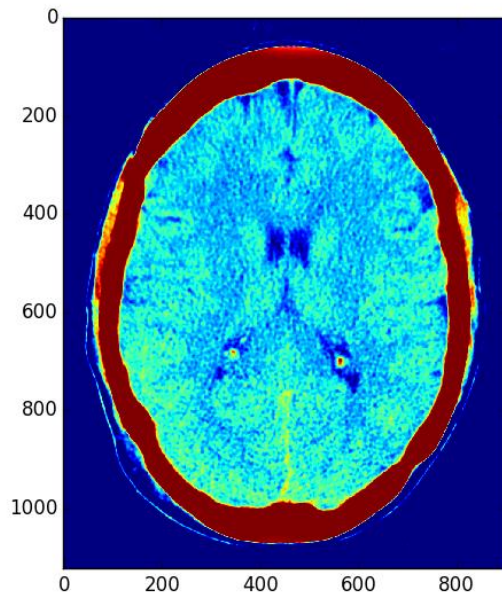
- Set no normalization

- Bind texture to sinogram

calculate image backprojection (parallelize slide 39)

- **Result: 200-250x speedup! (or more)**

- Result: 200-250x speedup! (or more)



Admin

- This topic is harder than before!
 - Lots of information
 - I may have missed something
- If there's anything unclear, let us know
 - I can (and likely will) make additional slides/explanatory materials

Admin

- C/CUDA code should work on all machines
- Pre/post-processing:
 - Python scripts preprocess.py, postprocess.py
 - (To run Python scripts: “python <script>.py”)
 - Either:
 - Use haru
 - Install python, (optionally pip) -> numpy, scipy, matplotlib, scikit-image

Resources

- Imaging methods:
 - [X-Ray CT in Nuclear Medicine](#)
 - [CT Image Reconstruction \(Peters, at AAPM\)](#)
 - [Elements of Modern Signal Processing \(Candes, at Stanford\)](#)
 - Proof that our algorithm works!