# An introduction to Plasma Tomography

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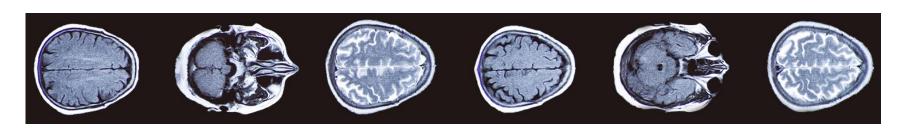


# **Computed Tomography**

Medical applications



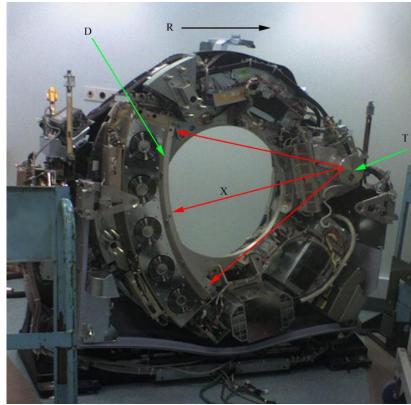




## Computed Tomography

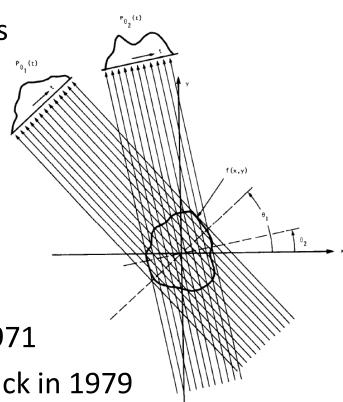
CT scanner internals



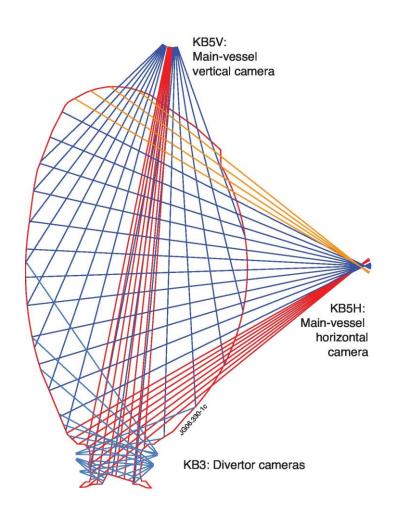


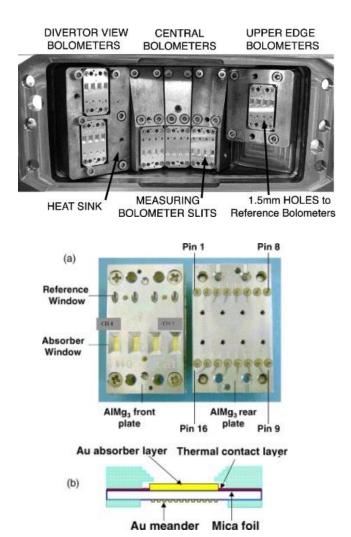
#### Computed Tomography

- Tomography problem
  - reconstruct image from its projections
    - each projection at a different angle
    - integral of the image at that angle
  - paper by J. Radon in 1917
    - Radon transform
    - inverse Radon transform
  - algorithm by A. Cormack in 1963-64
  - first CT scanner by G. Hounsfield in 1971
  - Nobel prize for Hounsfield and Cormack in 1979

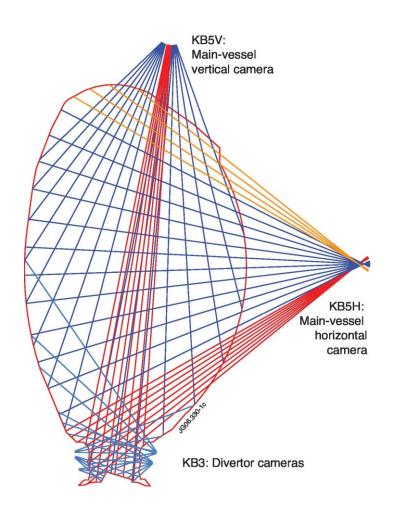


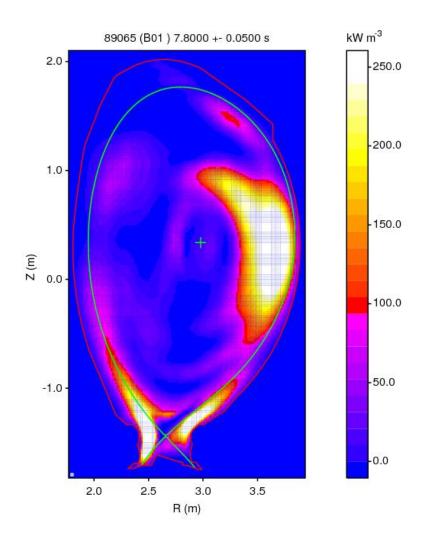
Tomography at the Joint European Torus (JET)



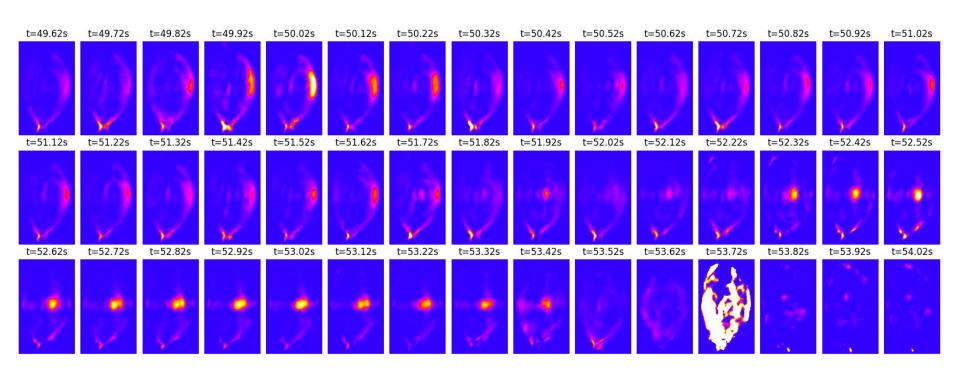


Tomography at the Joint European Torus (JET)





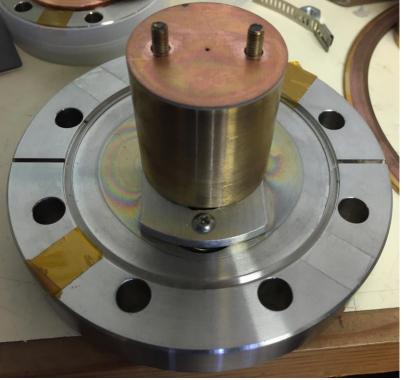
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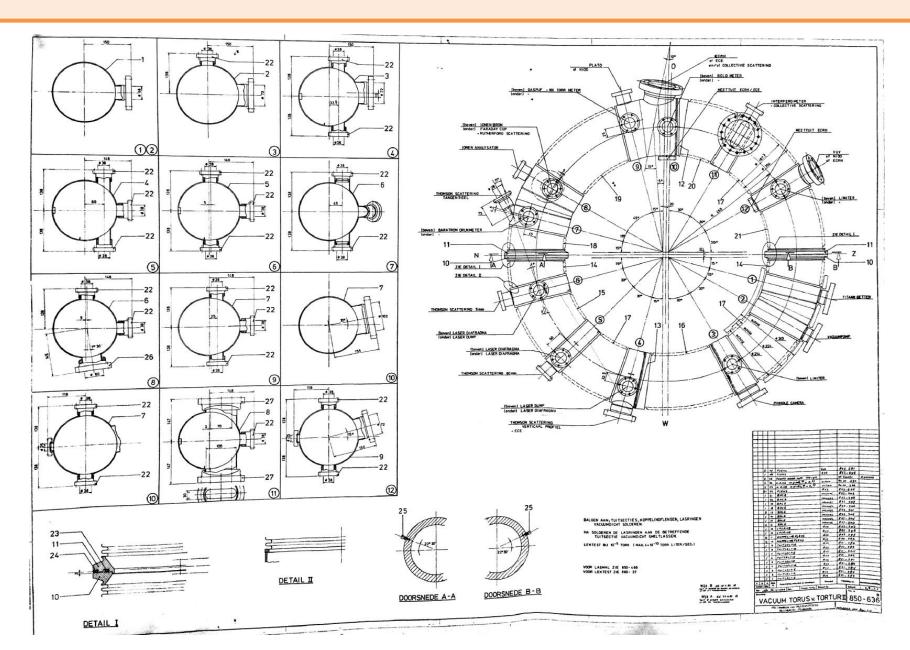


- Tomography at ISTTOK
  - cameras based on photodiode array + pinhole

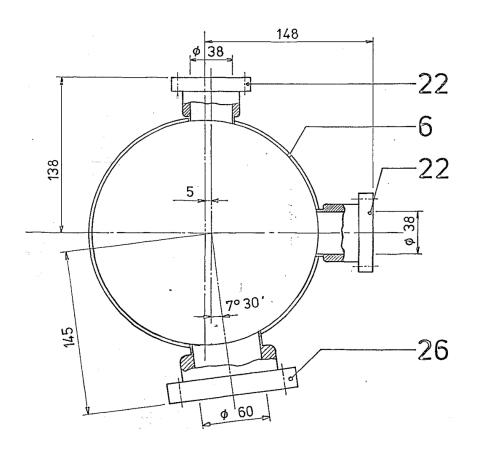






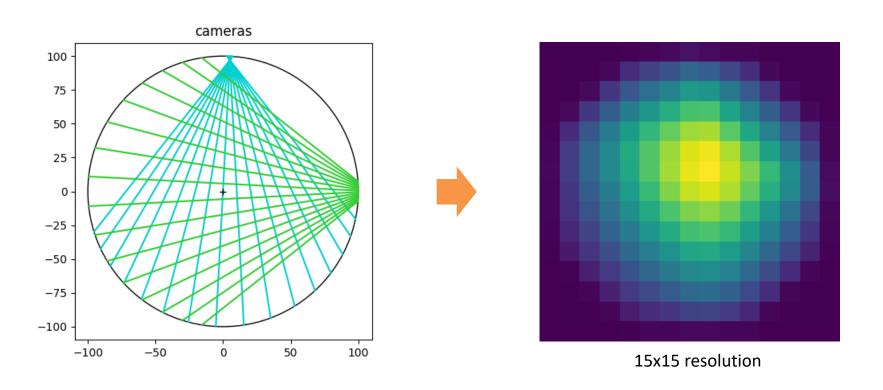


- ISTTOK setup (2019)
  - 2 cameras
    - vertical, horizontal
  - 16 detectors per camera
    - in fact 20 detectors, but
      4 are not used
  - lines of sight can be derived from detector and pinhole positions

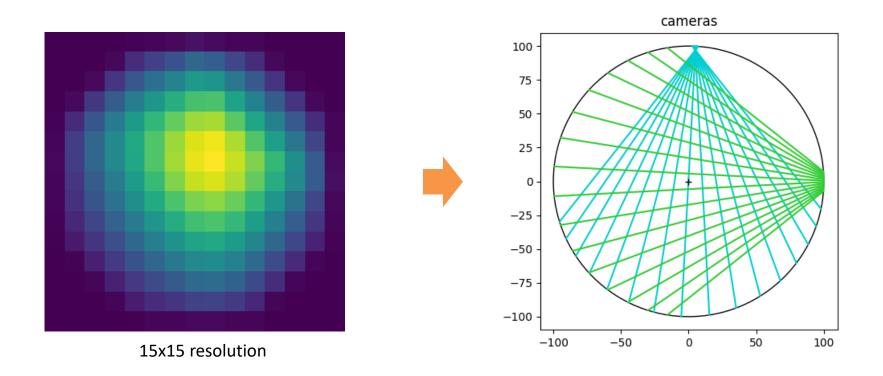


- Tomography methods
  - analytical methods (Fourier-based)
    - Fourier slice theorem
    - filtered backprojection (FBP)
    - Cormack's approach with basis functions
  - algebraic methods (pixel-based)
    - system of linear equations
    - iterative reconstruction techniques such as ART
    - solutions using regularization

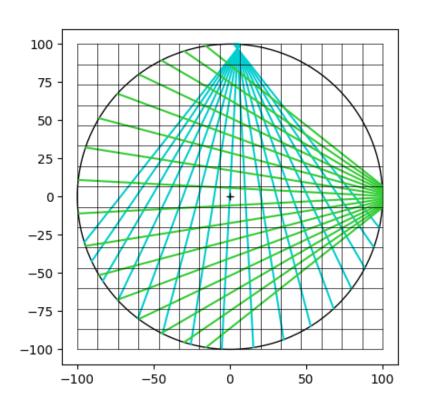
- Inverse problem
  - from detector measurements to plasma profile

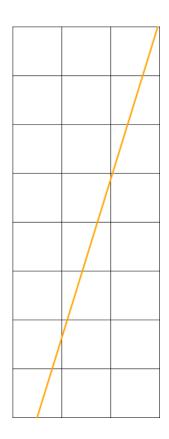


- Forward problem
  - from plasma profile to detector measurements

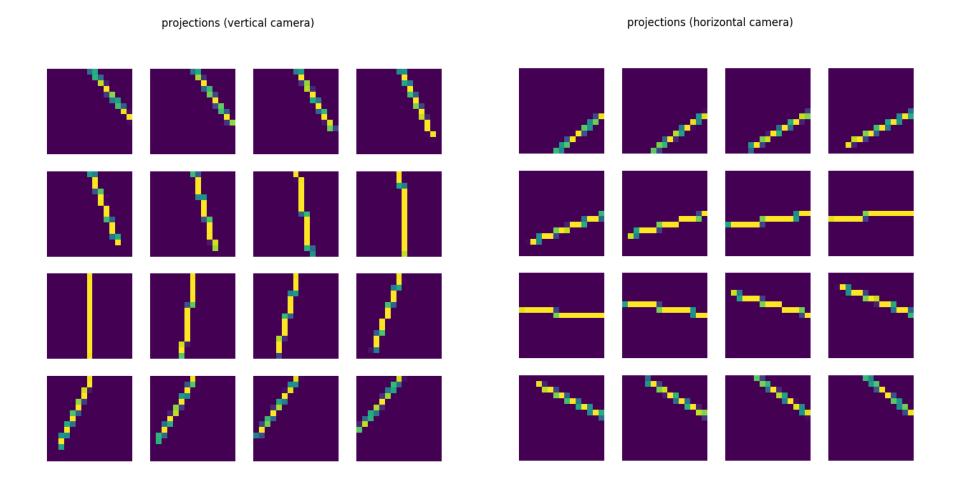


- Geometry of the problem
  - find the contribution of each pixel for each line of sight

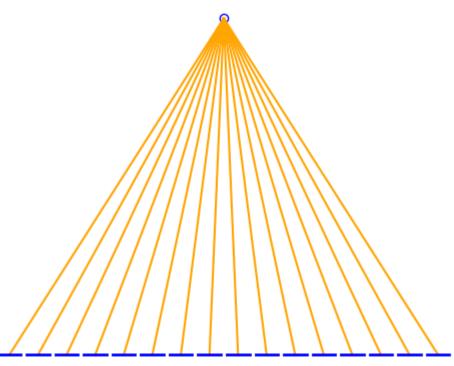


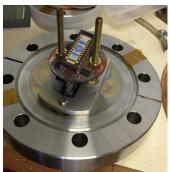


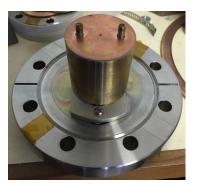
Contribution of each pixel to each line of sight



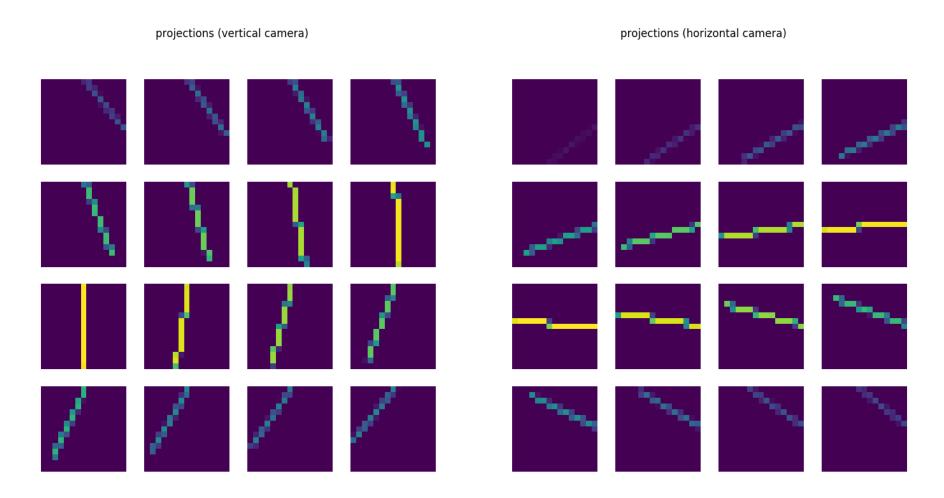
- Calibration factors (étendue)
  - angle of incidence on the detector
  - angle through the pinhole (and thickness)



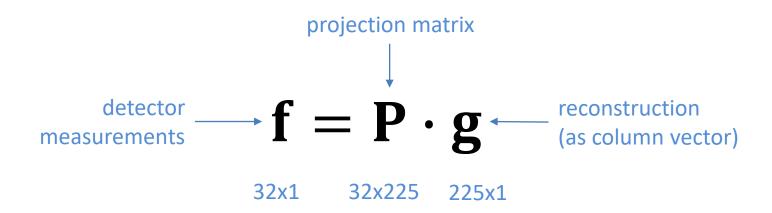




Contribution of each pixel to each line of sight

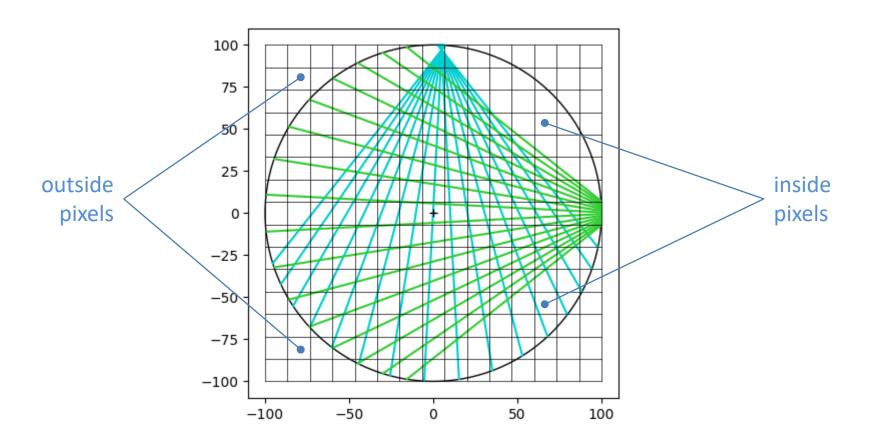


#### • In matrix form:



underdetermined system (32 equations for 225 unknowns)

Underdetermined system



- Regularization (general)
  - minimize:

$$\phi = \|\mathbf{f} - \mathbf{P}\mathbf{g}\|^2 + \alpha \|\mathbf{R}\mathbf{g}\|^2$$

$$\frac{\partial \phi}{\partial \mathbf{g}} = 0 \Rightarrow \mathbf{g} = (\mathbf{P}^{\mathrm{T}}\mathbf{P} + \alpha \mathbf{R}^{\mathrm{T}}\mathbf{R})^{-1}\mathbf{P}^{\mathrm{T}}\mathbf{f}$$

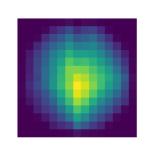
$$\mathbf{g} = (\mathbf{P}^{\mathrm{T}}\mathbf{P} + \alpha_{1}\mathbf{R}_{1}^{\mathrm{T}}\mathbf{R}_{1} + \alpha_{2}\mathbf{R}_{2}^{\mathrm{T}}\mathbf{R}_{2} + \cdots)^{-1}\mathbf{P}^{\mathrm{T}}\mathbf{f}$$

- Regularization (simple approach)
  - for every pixel
    - minimize the horizontal and vertical differences to neighbors
  - for outside pixels
    - minimize their norm

$$\phi = \|\mathbf{f} - \mathbf{P}\mathbf{g}\|^2 + \alpha_1 \|\mathbf{D}_{\mathbf{h}}\mathbf{g}\|^2 + \alpha_2 \|\mathbf{D}_{\mathbf{v}}\mathbf{g}\|^2 + \alpha_3 \|\mathbf{I}_{\mathbf{o}}\mathbf{g}\|^2$$

$$\mathbf{g} = (\mathbf{P}^{\mathrm{T}}\mathbf{P} + \alpha_{1}\mathbf{D}_{\mathrm{h}}^{\mathrm{T}}\mathbf{D}_{\mathrm{h}} + \alpha_{2}\mathbf{D}_{\mathrm{v}}^{\mathrm{T}}\mathbf{D}_{\mathrm{v}} + \alpha_{3}\mathbf{I}_{\mathrm{o}}^{\mathrm{T}}\mathbf{I}_{\mathrm{o}})^{-1}\mathbf{P}^{\mathrm{T}}\mathbf{f}$$

• Regularization matrix  $\mathbf{D}_h$ 



	Γ1	<b>-</b> 1	0	0	0	• • •	0	ر 0
	0	1	<b>-</b> 1	0	0		0	0
	0	0	1	<b>-</b> 1	0		0	0
	0	0	0	1	<b>-</b> 1		0	0
225x225	0	0	0	0	1		0	0
	:					•••		
	0	0	0	0	0		<b>-</b> 1	0
	0	0	0	0	0		1	-1
	L-1	0	0	0	0	• • •	0	1

• Regularization matrix  $\mathbf{D}_{\mathbf{v}}$ 

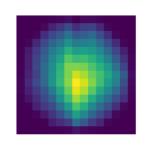


```
15 pixels
0
   0
           0
                    0
                       0
                               0
                                    0
            0
                    0
                               0
                                                            0
0
   0
           0
                    0
                       0
                               0
                                    0
                                                            0
                                0
                                                            0
                                        0
```

225x225

• Regularization matrix  $I_o$ 

225x225



1	U	U	• • •	U	U	U	• • •	U	U	U
0	1	0		0	0	0		0	0	0
0	0	1	•••	0	0	0	• • •	0	0	0
:		:		:		:		:		:
0	0	0	•••	0	0	0	• • •	0	0	0
0	0	0		0	0	0		0	0	0
0	0	0	•••	0	0	0	• • •	0	0	0
:		:		:		:		:		:
0	0	0	•••	0	0	0	• • •	1	0	0
0	0	0		0	0	0		0	1	0
L0	0	0	• • •	0	0	0	• • •	0	0	1

- Tomographic inversion
  - one reconstruction

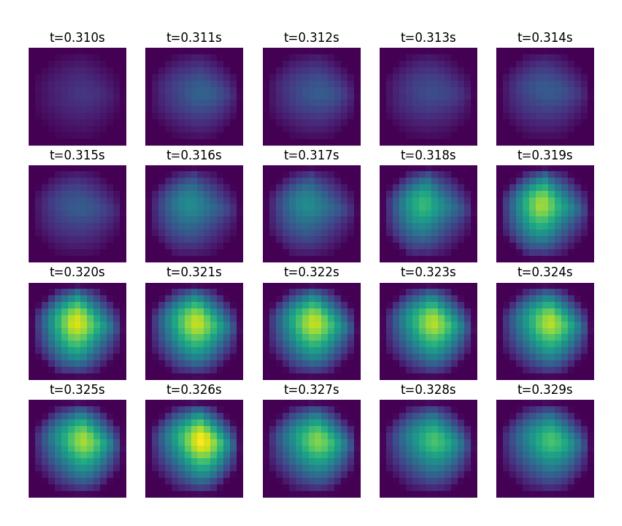
$$\mathbf{g} = (\mathbf{P}^{\mathrm{T}}\mathbf{P} + \alpha_{1}\mathbf{D}_{\mathrm{h}}^{\mathrm{T}}\mathbf{D}_{\mathrm{h}} + \alpha_{2}\mathbf{D}_{\mathrm{v}}^{\mathrm{T}}\mathbf{D}_{\mathrm{v}} + \alpha_{3}\mathbf{I}_{\mathrm{o}}^{\mathrm{T}}\mathbf{I}_{\mathrm{o}})^{-1}\mathbf{P}^{\mathrm{T}}\mathbf{f}$$

multiple reconstructions

$$\mathbf{M} = (\mathbf{P}^{\mathrm{T}}\mathbf{P} + \alpha_{1}\mathbf{D}_{\mathrm{h}}^{\mathrm{T}}\mathbf{D}_{\mathrm{h}} + \alpha_{2}\mathbf{D}_{\mathrm{v}}^{\mathrm{T}}\mathbf{D}_{\mathrm{v}} + \alpha_{3}\mathbf{I}_{\mathrm{o}}^{\mathrm{T}}\mathbf{I}_{\mathrm{o}})^{-1}\mathbf{P}^{\mathrm{T}}$$

$$\mathbf{g} = \mathbf{M} \cdot \mathbf{f}$$

Tomographic reconstructions for shot 47238



- Source code
  - available at: <a href="https://github.com/diogoff/isttok-tomography">https://github.com/diogoff/isttok-tomography</a>
  - cameras.py
    - finds the lines of sight for a given geometry
  - projections.py
    - finds the projection matrix for a given pixel resolution
  - signals.py
    - reads the camera signals for a given shot number
  - reconstructions.py
    - calculates the reconstructions at given times

- Other forms of regularization
  - generic
    - e.g. minimum Fisher information (MFI)
  - specific
    - e.g. smoothness along magnetic flux surfaces

Minimum Fisher information (MFI)

$$I_F = \int \frac{g'(x)^2}{g(x)} dx$$

- inspired by the concept of Fisher information
- differences should be small, but they are allowed to be larger where g itself is large

$$\mathbf{g} = (\mathbf{P}^{\mathrm{T}}\mathbf{P} + \alpha_{1}\mathbf{D}_{h}^{\mathrm{T}}\mathbf{D}_{h} + \alpha_{2}\mathbf{D}_{v}^{\mathrm{T}}\mathbf{D}_{v} + \alpha_{3}\mathbf{I}_{o}^{\mathrm{T}}\mathbf{I}_{o})^{-1}\mathbf{P}^{\mathrm{T}}\mathbf{f}$$

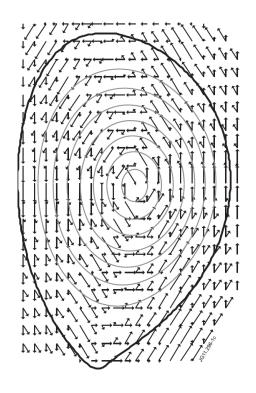
$$\mathbf{D}_{h}^{\mathrm{T}}\mathbf{D}_{h} \rightarrow \mathbf{D}_{h}^{\mathrm{T}}\mathbf{W}\mathbf{D}_{h}$$

$$\mathbf{D}_{v}^{\mathrm{T}}\mathbf{D}_{v} \rightarrow \mathbf{D}_{v}^{\mathrm{T}}\mathbf{W}\mathbf{D}_{v}$$

$$\mathbf{W} = diag\left(\frac{1}{\mathbf{g}}\right)$$

system becomes non-linear; solve iteratively for g

- Smoothness along magnetic flux surfaces
  - differences are taken along the direction of magnetic flux surfaces
  - plasma equilibrium (e.g. by EFIT) must be provided beforehand
  - system remains linear but now depends on data from other diagnostics



$$\mathbf{g} = (\mathbf{P}^{\mathrm{T}}\mathbf{P} + \alpha_{1}\mathbf{D}_{h}^{\mathrm{T}}\mathbf{D}_{h} + \alpha_{2}\mathbf{D}_{v}^{\mathrm{T}}\mathbf{D}_{v} + \alpha_{3}\mathbf{I}_{o}^{\mathrm{T}}\mathbf{I}_{o})^{-1}\mathbf{P}^{\mathrm{T}}\mathbf{f}$$

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