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)



t=49.68s	t=49.72s	t=49.76s	t=49.80s	t=49.84s	t=49.88s	t=49.92s	t=49.96s	t=50.00s	t=50.04s	t=50.08s	t=50.12s	t=50.16s	t=50.20s	t=50.24s
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- Tomography at ISTTOK
 - cameras based on photodiode array + pinhole







- ISTTOK setup (2009)
 - 3 cameras
 - top, front, bottom
 - 8 detectors per camera
 - in fact 10 detectors, but
 2 are hidden
 - 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

- Reconstruction from detector measurements
 - inverse problem





- Detector measurements from given reconstruction
 - forward problem



15x15 resolution



• Contribution of each pixel to each detector





• Contribution of each pixel to each detector

projections (top camera)



• Contribution of each pixel to each detector

projections (front camera)



• Contribution of each pixel to each detector

projections (bottom camera)



• In matrix form:



underdetermined system (24 equations for 225 unknowns)

Underdetermined system



- Regularization (general)
 - minimize:

$$\phi = \|\mathbf{f} - \mathbf{P}\mathbf{g}\|^2 + \alpha \|\mathbf{R}\mathbf{g}\|^2$$
$$\frac{\partial \phi}{\partial \mathbf{g}} = 0 \implies \mathbf{g} = (\mathbf{P}^{\mathrm{T}}\mathbf{P} + \alpha \mathbf{R}^{\mathrm{T}}\mathbf{R})^{-1}\mathbf{P}^{\mathrm{T}}\mathbf{f}$$

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

- 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



$$225 \times 225 \begin{bmatrix} 1 & -1 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ \vdots & & & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & 0 \\ -1 & 0 & 0 & 0 & 0 & \cdots & 0 & 1 \end{bmatrix}$$

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225x225

• Regularization matrix I_o



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24

- 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 17552



- Source code
 - available at: <u>https://github.com/diogoff/isttok-tomography</u>
 - 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

$$\begin{split} \mathbf{g} &= (\mathbf{P}^{\mathrm{T}}\mathbf{P} + \alpha_{1}\mathbf{D}_{\mathrm{h}}^{\mathrm{T}}\mathbf{D}_{\mathrm{h}} + \alpha_{2}\mathbf{D}_{\mathrm{v}}^{\mathrm{T}}\mathbf{D}_{\mathrm{v}} + \alpha_{3}\mathbf{I}_{\mathrm{o}}^{\mathrm{T}}\mathbf{I}_{\mathrm{o}})^{-1}\mathbf{P}^{\mathrm{T}}\mathbf{f} \\ \mathbf{D}_{\mathrm{h}}^{\mathrm{T}}\mathbf{D}_{\mathrm{h}} \rightarrow \mathbf{D}_{\mathrm{h}}^{\mathrm{T}}\mathbf{W}\mathbf{D}_{\mathrm{h}} \\ \mathbf{D}_{\mathrm{v}}^{\mathrm{T}}\mathbf{D}_{\mathrm{v}} \rightarrow \mathbf{D}_{\mathrm{v}}^{\mathrm{T}}\mathbf{W}\mathbf{D}_{\mathrm{v}} \qquad \mathbf{W} = diag\left(\frac{1}{g}\right) \end{split}$$

- 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



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

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