

ToFu

An open-source python/cython library for synthetic
tomography diagnostics on tokamaks

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Context

Context: energy needs vs climate change



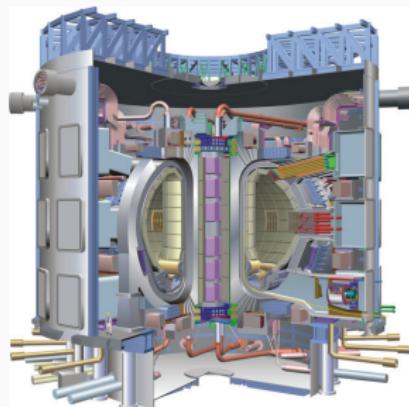
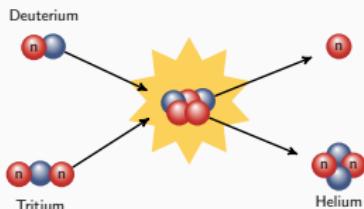
Current solutions present some drawbacks:

- limited or intermittent resources
- Production of carbon dioxide
- significant production of green house gases or radioactive waste
- not too efficient
- harmful to surrounding environment
- low availability without long-term mass storage solution
- unequal geographical distribution of resources
- industrial risks (nuclear, chemical...)

⇒ **Fusion**: cleaner, more reliable, more powerful energy source?

Context: Controlled fusion and magnetic confinement

D-T Fusion reaction



- Gas > 100 Million°K composed of positive ions and negative electrons: plasma
- Confinement using electromagnetic fields
- break-even not obtained yet
- Current reactors: different shapes, sizes, heating methods, confinement techniques, etc.

Tomography diagnostics

Tokamak diagnostics to measure plasma quantities

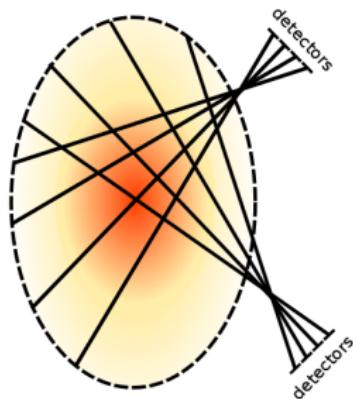
Diagnostics

Set of instruments to measure for the understanding, control and optimization of the plasma performance.

- **Magnetic** diagnostics: currents, plasma stored energy, plasma shape and position;
- **Neutron** diagnostics (ie. cameras, spectrometers, etc.): fusion power;
- Optical systems (**interferometers**): temperature and density profiles;
- Bolometric systems (**tomography**): spatial distribution of radiated power;
- **Spectroscopic**: X-ray wavelength range, impurity species and density, input particle flux, ion temperature, helium density, fueling ratio, plasma rotation, and current density.

Tomography diagnostics - numerical context

$$M_i(t) = \iiint_{V_i} \overrightarrow{\varepsilon(x,t)} \cdot \vec{n} \Omega_i \, dV$$



- **Direct problem** (synthetic diagnostic):

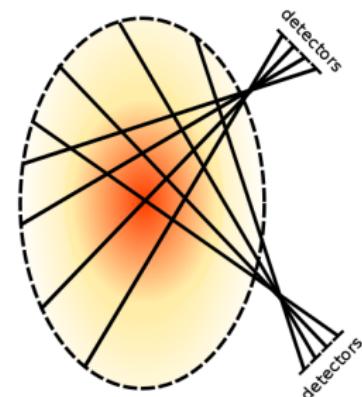
Simulated emissivity \longrightarrow integrated measurements

- **Inverse problem** (tomography):

Integrated measurements \longrightarrow Reconstructed emissivity

Tomography diagnostics - numerical context

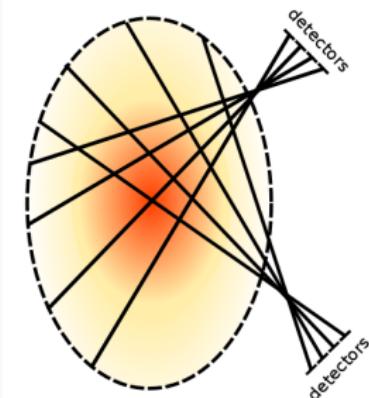
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- **Direct problem** (synthetic diagnostic):
Simulated emissivity → measurements
Spatial integration
- **Inverse problem** (tomography):
Integrated measurements → Reconstructed emissivity
Mesh and basis functions construction, spatial integration, data filtering, inversion routines, etc.

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Tomography very sensitive to errors, noise and bias
→ Reputation for low reproducibility / reliability

The ToFu code

Motivation: “current” state

In the fusion community, codes for synthetic diagnostic are developed:

- by physicists (with little to no programming experience),
- in Matlab,
- from scratch,
- in local/private

... which means

- repetition of work: lost time, man-power, etc;
- no traceability,
- results impossible to reproduce,
- no standardization of diagnostics

A code for Tomography for Fusion

Develop a common tool:

- Accessible to everyone (open-source)
- Generic (geometry independent)
- Portable (developed in Python)
- Optimized (reliability and performance)
- Documented online
- Continuous integration



For tomography diagnostics:

The **Tomography for Fusion** code (**ToFu**¹²³)

¹repository: <https://github.com/ToFuProject/tofu>

²documentation: <https://tofuproject.github.io/tofu/index.html>

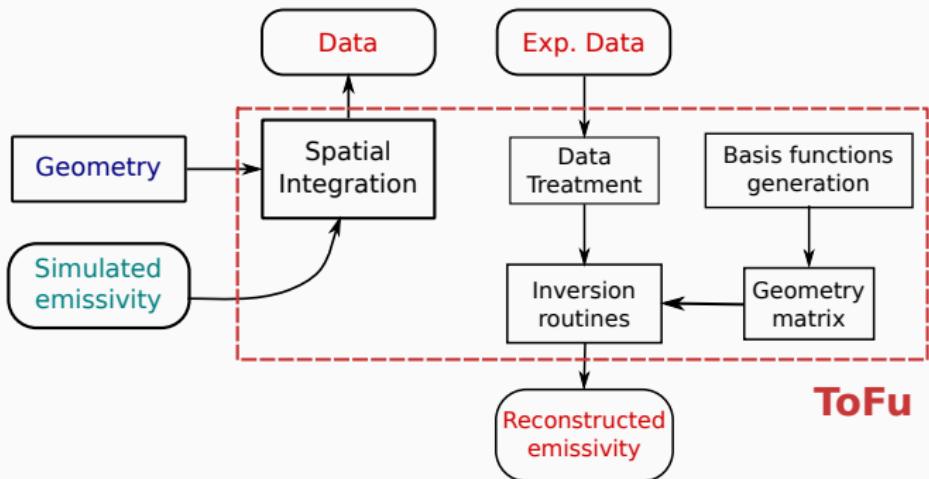
³ D Vezinet et al. "Non-monotonic growth rates of sawtooth precursors evidenced with a new method on ASDEX Upgrade". In: *Nuclear Fusion* 8 (2016).

More about Tofu

- Created in 2014
- Open Source: **MIT license**
- Python 2.7 and **Python 3 + Cython**
- Continuous integration: **Travis CI**
- **conda, pip**
- Two (main) developers:
 - ▶ Didier Vezinet (creator, PhD in Physics)
 - ▶ Laura S. Mendoza (since June 2018, PhD in Applied Mathematics)
- Contributors:
 - ▶ Jorge Morales (PhD in Physics)
 - ▶ Florian Le Bourdais
 - ▶ Arpan Khandelwal (intern)



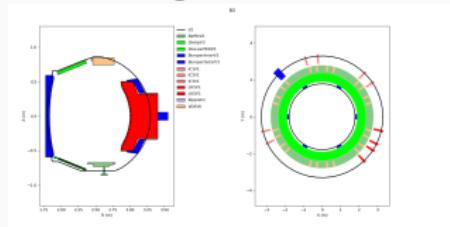
Tofu's structure



ToFu

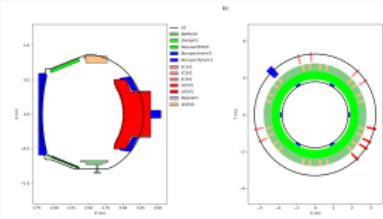
What ToFu can do: modeling of simplified geometry

Geometry configuration

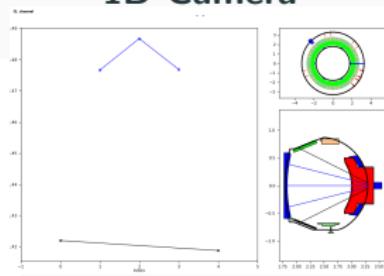


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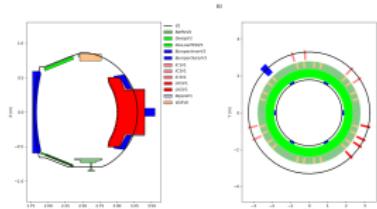


1D Camera

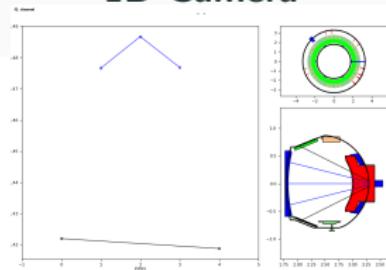


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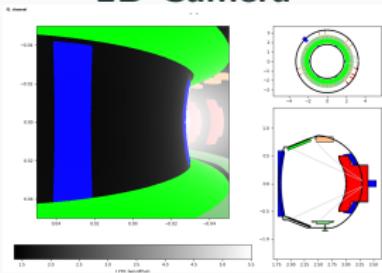
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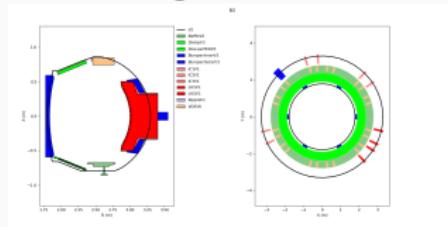


2D Camera



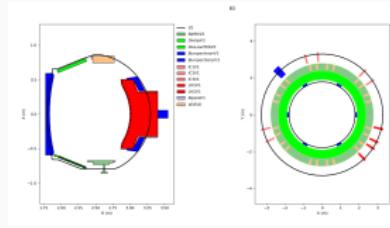
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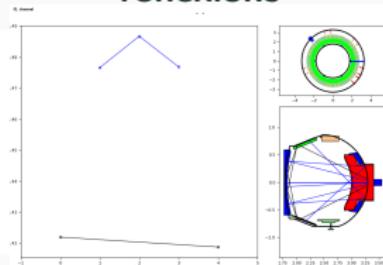


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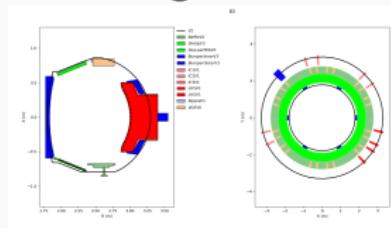


1D Camera with reflexions

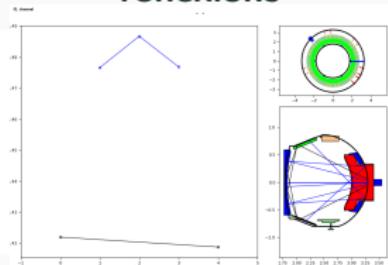


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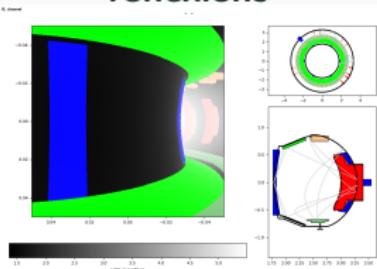
Geometry configuration



1D Camera with reflexions



2D Camera with reflexions



What ToFu can do

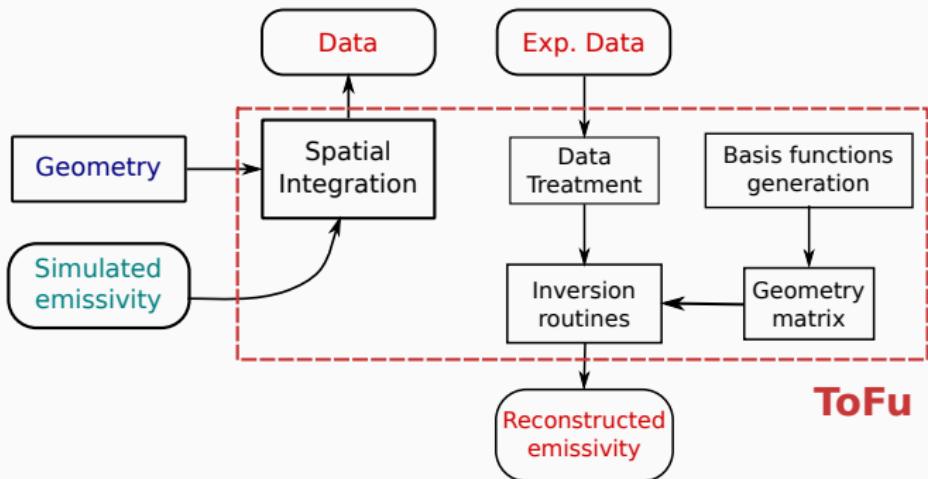
ToFu can:

- Modeling of simplified geometry
- 3D modeling of a 1D camera
- 3D modeling of a 2D camera
- Handle basic reflexions
- Computing synthetic signals
- ...and soon:
 - ▶ meshing and basis functions
 - ▶ tomographic inversion
 - ▶ dust particle trajectory tracking
 - ▶ faster Matplotlib + PyQtGraph visualization
 - ▶ magnetic field line tracing
 - ▶ data visualization and statistical tools (pandas)

Demo

Demo

Tofu's structure



ToFu

Optimization of the code

Geometry reconstruction: ray-tracing techniques

To reconstruct emissivity we need to take account:

- Up to hundreds of structural elements in vessel
 - Scale of the vessel: 10^4 bigger than smaller structural detail
- ⇒ Geometry defined with minimal data polygon (R, Z)
extruded along φ
- ⇒ Symmetry of vessel along φ



Optimization of ray-tracing algorithm

- Description of geometry:

- ▶ Vessel and structures: set of 2D polygon

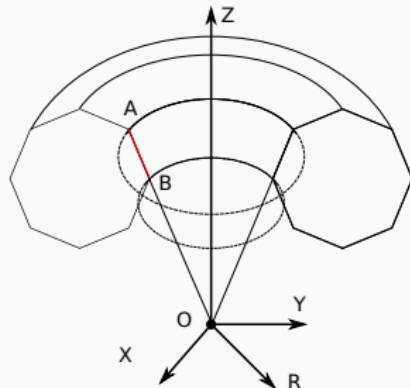
$$\mathcal{P}_j = \bigcup_{i=1}^n \overline{A_i B_i}$$

- ▶ Extruded along $[\varphi_{min}, \varphi_{max}]$

- ▶ Detectors defined as set of rays (of origin D and direction u)

⇒ Light memory-wise

⇒ Equivalent to: set of truncated cones
(frustums) of generatrix $A_i B_i$



Ray-tracing algorithm on fusion device → Computation of cone-Ray intersection

$$\exists (q, k) \in [0; 1] \times [0; \infty[, \quad \left\{ \begin{array}{l} R - R_A = q(R_B - R_A) \\ Z - Z_A = q(Z_B - Z_A) \\ DM = ku \end{array} \right.$$

Optimization of ray-tracing algorithm

Cone-Ray intersection algorithm:

- Main steps:
 - ▶ Test intersection **bounding-box**
 - ▶ **special cases** (ray direction, segment, etc.)
 - ▶ General case: solution of a **quadratic equation**
- Pre-computation of variables
- Core functions in **Cython**
- Parallelization (**prange** loops)

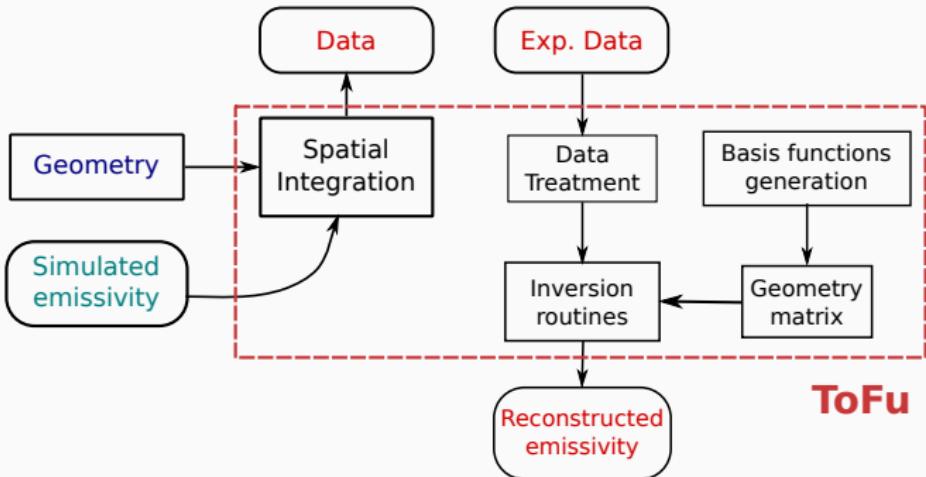
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Nb LOS	10^3	10^4	10^5	10^6	
original	$3.26 \cdot 10^1$	$3.10 \cdot 10^2$	$3.20 \cdot 10^3$	$3.17 \cdot 10^4$	(8h48)
optimized	$2.58 \cdot 10^{-2}$	$2.72 \cdot 10^{-1}$	2.74	$2.66 \cdot 10^1$	(< 30s)
32 threads	$1.36 \cdot 10^{-2}$	$4.66 \cdot 10^{-2}$	$3.64 \cdot 10^{-1}$	2.92	

Tofu's structure



Optimization of spatial integration routines

Integration of **user-defined function** along a LOS:

- Integration of a python function **func** defined by user by:
 - ▶ **numpy.sum** (quad: **midpoint**)
 - ▶ Cython based sum (quad: **midpoint**)
 - ▶ **Scipy.integrate.simps**
 - ▶ **Scipy.integrate.romb**
- Optional optimizations:
 - ▶ calls to **func**: avoid Cython-Python conversion, user-defined
 - ▶ memory: fine resolutions, high number of LOS
 - ▶ hybrid: compromise

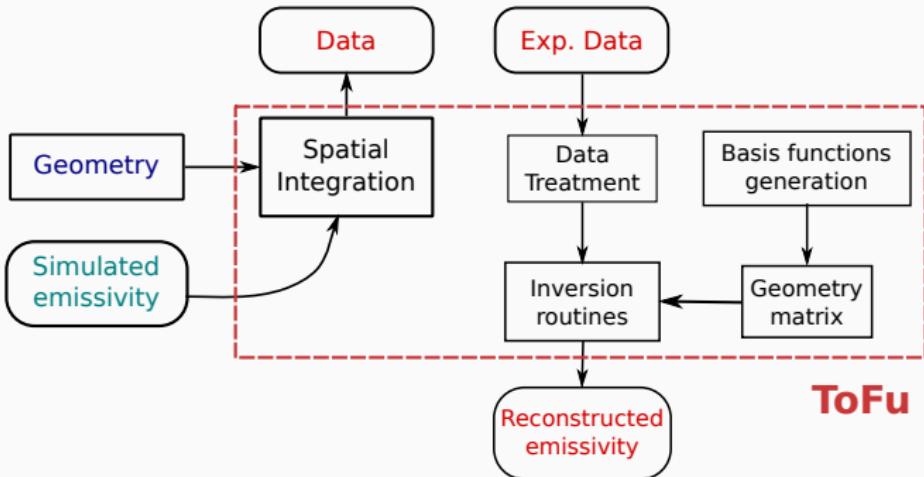
Optimization of spatial integration routines

LOS	10	10^2	10^3	10^4
original	0.46	2.24	18.1	x
memory	0.9	8.9	96	945 (6Gb)
calls	0.207	0.53	4.32	x
hybrid	0.08	0.44	4.2	40.3 (32Gb)

- Space resolution: 10^{-3}
- Number of time steps: 10^3
- Integration method: **sum** (Cython or numpy) on midpoint

What's next

Tofu's structure



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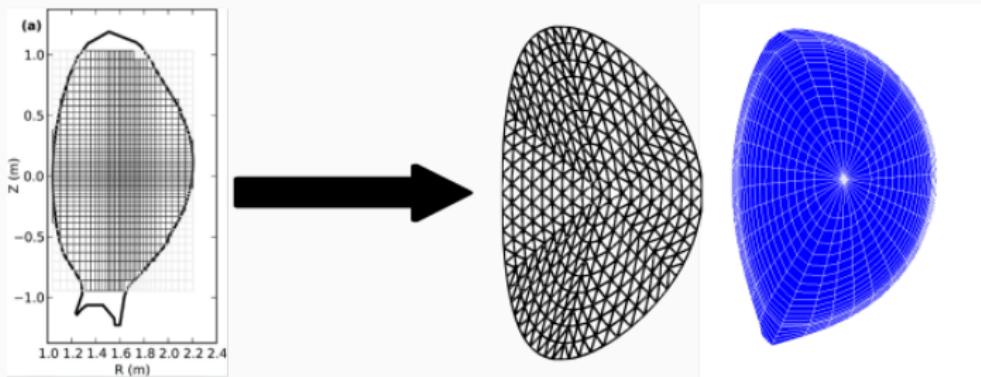
On geometry discretization: meshing

Several options for poloidal cut meshing:

- Cartesian mesh
- Polar mesh
- Adaptive polar mesh
- Hexagonal mesh
- Triangular mesh

For basis functions:

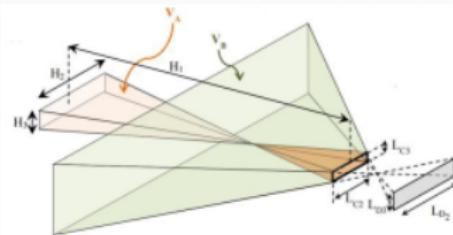
- Lagrange polynomials
- B-splines
- NURBS
- Box-splines



Tofu's main algorithms

Visualization and geometrical tools:

- Ray-tracing algorithm
- Distance 3D objects and rays
- Vignetting: 3D polygon - Ray
- Solid angles computation (reflexions)



For direct and inverse problem:

- Basis functions
- Discretization: Geometry, Lines, Volumes
- Spatial integration
- Regularization-inversion routines (Bayesian, non linear, etc.)
- Filtering

Thank you for your attention!

B(asis)-Splines basis*

B-Splines of degree d are defined by the **recursion formula**:

$$B_j^{d+1}(x) = \frac{x - x_j}{x_{j+d} - x_j} B_j^d(x) + \frac{x_{j+1} - x}{x_{j+d+1} - x_{j+1}} B_{j+1}^d(x) \quad (1)$$

Some important properties about B-splines:

- Piece-wise polynomials of degree $d \Rightarrow$ **smoothness**
- Compact support \Rightarrow **sparse matrix system**
- Partition of unity $\sum_j B_j(x) = 1, \forall x \Rightarrow$ **conservation laws**

