30th May 2019
3rd IAEA Technical Meeting on Fusion Data Processing, Validation and Analysis
Analysis of Scrape-Off Layer Filament Properties Using Visible Camera Data


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The importance of filaments

• Filamentary structures occur in the boundary of magnetic fusion devices in all regimes of operation.
• Affect the plasma-wall interaction producing localized loads and erosion.
• Proper measurements of their dynamics and statistics are essential for their theoretical and empirical understanding.
• Filaments in MAST were easily detectable due to their natural light emission and wide angle view.
• Not just pretty movies, they are full of information on the physics of the boundary plasma.
## Filament measurement diagnostics

<table>
<thead>
<tr>
<th></th>
<th>Reciprocating Langmuir probe (RCP)</th>
<th>Beam emission spectroscopy (BES)</th>
<th>Gas puff imaging (GPI)</th>
<th>Visible imaging (VI)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description</strong></td>
<td>Ion saturation current</td>
<td>Emission for neutral beam injection</td>
<td>Emission from local neutral gas puff</td>
<td>Unfiltered ($D_\alpha$) light</td>
</tr>
<tr>
<td><strong>Spatial dimensions</strong></td>
<td>0D/1D</td>
<td>1D/2D</td>
<td>2D</td>
<td>3D</td>
</tr>
<tr>
<td><strong>Temporal durations [ms]</strong></td>
<td>Reciprocation ~400</td>
<td>Duration of beam</td>
<td>Duration of gas puff ~80</td>
<td>Whole pulse</td>
</tr>
<tr>
<td><strong>Spatial extent [cm]</strong></td>
<td>20</td>
<td>25 × 20</td>
<td>24 × 30</td>
<td>25 × 100 +</td>
</tr>
<tr>
<td><strong>Temporal resolution [MHz]</strong></td>
<td>~2 +</td>
<td>~0.4</td>
<td>~0.4</td>
<td>~0.2</td>
</tr>
<tr>
<td><strong>Spatial resolution [cm]</strong></td>
<td>N/A</td>
<td>~3 × 3</td>
<td>~0.4</td>
<td>~0.5</td>
</tr>
<tr>
<td><strong>Perturbative/passive</strong></td>
<td>Requires probe reciprocation</td>
<td>Requires beam</td>
<td>Requires gas puff</td>
<td>Passive</td>
</tr>
</tbody>
</table>

![Graph](image1.png)  
![Graph](image2.png)  
![Image](image3.png)

[Smith et al., RSI, 2010]  
[Garcia et al., NF, 2015]  
[Zweben et al., NF, 2015]
Elzar inversion and filament detection code

- The **Elzar code** uses the known structure of the magnetic field to map the amplitude of light emission from camera images onto radial and toroidal field line coordinates.
- **Elzar** then detects the filaments as blobs of light and analyses their statistics.

Elzar inversion

Camera image

Elzar representation

Radial direction, $R$

Toroidal angle, $\phi$

Core, Scrape Off Layer
Mathematical representation of inversion technique

Assume camera images can be represented by linear superposition of images of uniformly emitting individual magnetic equilibrium field-lines.

Camera image \( i \) = Elzar representation \( [B]w \)

- Camera image
- Vector of pixels
- Basis functions
- Matrix of field line images
- Elzar mapping
- Vector of field line intensities
- Set of basis functions

\[ i = [B]w \]
**Approximate inversion technique**

- As common in tomographic problems, the system is **overdetermined**
  - Look for approximate solution using **ordinary least squares** approach

  \[ w \cong [B]^+ i \]

  \[ [B]^+ \equiv ( [B]^T [B] )^{-1} [B]^T \]

  \[ \Rightarrow w \cong ( [B]^T [B] )^{-1} \underbrace{[B]^T i}_{\text{vector}} \]

- We look for \( i \) such that \( |i - w[B]| \) is minimized
- Solve using **non-negative SART** algorithm with **Laplacian regularisation**
- Works with a **subset of toroidal coverage**
- Allows use of **smaller and lower resolution matrices**
Filament detection algorithm

- The **watershed algorithm** is used to identify the filaments in the inverted image.

- **2D Gaussians** are fitted to each detected filament recording:
  - Position (center of the Gaussian)
  - Width (axes of the Gaussian)
  - Amplitude (amplitude of Gaussian)
Synthetic data and their use

- We can generate synthetic frames and then apply the approximate inversion technique:

\[ i_{syn} = [B]w_{syn} \implies w \cong [B]^+ i_{syn} \]

- We know the exact position and size of the filaments
- Using our detection algorithm on the set of synthetic images we can
  - Assess performance
  - Quantify errors
Detection precision and sensitivity using synthetic data

- **Precision** of detections
  - “What proportion of detections are real synthetic filaments?”
  
  $f_{\text{prec}} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$

- **Sensitivity** to all filaments
  - “What proportion of the total filament population do we capture?”
  
  $f_{\text{sens, domain}} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$

- **Sensitivity** to isolated filaments
  - “What proportion of the filaments we intend to measure do we capture?”
  
  $f_{\text{sens, isolated}} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Negative}) \mid with \epsilon > \epsilon_{\text{thresh}}}$

Want to maximise figures of merit

![Graph showing detection precision and sensitivity](image)

- $98.8\%$
- $74\%$
- $36\%$
Error quantification with synthetic data

- Using the synthetic data, errors in the detected parameters are:
  - $e_p = \rho_{\text{measured, synthetic}} - \rho_{\text{true, synthetic}}$

- Every synthetic filament has a different error, hence we can build statistics

- Fit gaussians to residuals to identify
  - $\mu_p$ – Systematic offset error in measurements
  - $\sigma_p$ – Standard error from gaussian fit
  - $f_p = \left( \frac{|e_p|}{\rho_{\text{true}}} \right)$

### Quantity, $\rho$ | Error | $\mu_p$ | $\sigma_p$ | $f_p$
--- | --- | --- | --- | ---
$R - R_{sep}$ [mm] | 3 | 1 | 4% (7%) |
$R\phi$ [mm] | -3 | 2 | 15% (22%) |
$\delta_R$ [mm] | 6 | 3 | 33% (70%) |
$\delta_{R\phi}$ [mm] | 1.1 | 7 | 26% (67%) |

Note: results from synthetic data

Error distributions, $e_p$
Recovery of parameter distributions

Using the systematic errors just calculated, we apply corrections to the analysis.

We can now check if the Elzar approach captures the statistical distribution imposed on the synthetic data.

- Distributions of positions are well captured.
- Distributions of widths are qualitatively recovered.

Characterise changes.

Being able to capture the statistics of the filaments is important for model validation.
Example synthetic image

\[ \sigma = 5\% \text{ dynamic range} \]

Original synthetic frame

Noise \sim \frac{1}{\sqrt{2\pi \sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}

Experimental frame
Application of neural networks to ELZAR

- To improve the speed and quality of the detection and tracking, a convolutional neural network is used.
- Faster R-CNN algorithm used to efficiently detect features in Elzar inversions.
- Apply to Elzar maps rather than raw images for independence from the magnetic equilibrium.
Filament detection with neural networks

- **5,000 synthetic images** with 40,000 filaments were used in the training/testing of the network.

<table>
<thead>
<tr>
<th># Filaments</th>
<th>True Positive</th>
<th>False Negative</th>
<th>False Positive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Set</td>
<td>36743</td>
<td>26791</td>
<td>9952</td>
</tr>
<tr>
<td>Test Set</td>
<td>4143</td>
<td>3019</td>
<td>1124</td>
</tr>
</tbody>
</table>

\[
\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}
\]

\[
= 93\% \ (98.8\%)
\]

\[
\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}
\]

\[
= 73\% \ (36\%)
\]

\[
\times 2
\]

- **500,000 images generated**, now being processed by the network to further improve the detection quality.

c.f. watershed performance

5,000 synthetic images with 40,000 filaments were used in the training/testing of the network.
Application to Experimental Data: Filament statistics

— **Experimental** distributions consistent with past findings
  - Lognormal radial positions and widths
  - Exponential amplitudes above $\epsilon_{\text{thresh}}$

— **Inferred** possible true distributions informed by synthetic filament analysis

Note: results from experimental data
Comparison with Langmuir probe data

- Can take datasets with reduced dimensionality for comparison with Langmuir probes

- Intensity time series $I(t)$ at the separatrix, $r_{sep} = 0$ cm both show similar bursty behaviour

- Conditional averaging shows similar conditionally averaged waveforms
Evidence of spatial and temporal Poisson behaviour

- Camera depth of field uniquely enables simultaneous toroidally distinct measurements
- Filament waiting times and spatial separations both exponentially distributed
  - Exponential toroidal filament separations indicates filaments generated uniformly and independently
  - Important verification for analytic framework [Militello, PPCF, 2016]
- Peak in separations at \(~12\) cm
  - Consistent with filaments interacting within \(~5\) filament widths [Militello, PPCF, 2017]
A new tool to detect filaments from visual cameras has been developed at CCFE. The inversion employs the structure of the magnetic field lines as basis functions. Performance and error quantification were determined using synthetic images with filaments of given position, size, and amplitude. Good performance is achieved, even better with neural networks. Application to experiments allows determining the statistics of the filaments with unique flexibility. First results show uncorrelated filaments governed by Poisson statistics.
Outlook

Future work

• Explore filament parallel structure
• Apply technique to alternative camera views
• Apply technique to archive of MAST data
• Apply on MAST-U and other machines?
• Quantify errors from inaccuracies in
  • Magnetic equilibrium reconstruction
  • Camera calibrations
• Further develop and apply filament tracking techniques

Collaborations

• Stereoscopic MAST-U fast camera measurements (*William and Mary*)
  • Increase accuracy, quantify field aligned assumption
• Neural networks for filament detection (*University of Cagliari*)
  • Improve accuracy, reliability and speed of filament detections
A new camera tomographic inversion tool for detection of filaments

The inversion employs the structure of the magnetic field lines as basis functions

Performance and error quantification determined using synthetic images

Good performance is achieved, even better with neural networks

Unique flexibility to measure experimental filaments statistics

First results show uncorrelated filaments governed by Poisson statistics (exponential statistics)
Filament Tracking

- Check for filaments within fixed distance of previous filaments
- Each detected filament in the current frame is compared to all those in the next one.
- Filaments within fixed distance are matched.
- Blobs should move toroidally in the same direction of plasma rotation and radially outwards.
Filament Tracking

Connect chains of similar filaments in adjacent frames

Radial motion

Toroidal motion

Frame number

Frame number
Filament Tracking
Amplitude Variation

Longest lived filaments have largest peak amplitude
Amplitude peaks just outside separatrix

\[ \frac{A}{A_0} t [\mu s] \]

Low neutral density
Parallel drainage of flux tubes

Radial position (m)
Filament Lifetimes

Probability density

Lifetime [frames]
Toroidal Velocities

Weibull distributions of filament velocities

<table>
<thead>
<tr>
<th>Weibull distribution parameters</th>
<th>Toroidal velocity (km/s)</th>
<th>Radial velocity (km/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean [km s$^{-1}$]</td>
<td>3.8</td>
<td>0.8</td>
</tr>
<tr>
<td>Variance [km$^2$s$^{-2}$]</td>
<td>3.6</td>
<td>0.3</td>
</tr>
<tr>
<td>Scale (λ)</td>
<td>4.3</td>
<td>0.8</td>
</tr>
<tr>
<td>Shape (k)</td>
<td>2.1</td>
<td>1.4</td>
</tr>
</tbody>
</table>
Amplitude Variation

Toroidal widths well described by a log-normal distribution
Backup slides: Filament statistics and profiles
What are filaments?

Filaments are perturbations in plasma density and temperature which:
- Are aligned to the magnetic field
- Have large parallel dimensions relative to perpendicular dimensions
- Intermittent fluctuations

What do they do?

Dominate turbulent cross-field particle transport
- They propagate radially outwards far from the last closed flux surface (LCFS)
- Widen the scrape off layer (SOL)
- Increase particle transport to the walls
  - Typically responsible for >50% of SOL particle transport
    [D’Ippolito, PoP, 2011]
- Time average of filaments leads to SOL density profiles
The diffusion paradox

- One of the aims of turbulence theory is to correlate gradients with fluxes.

\[ \frac{\Gamma}{n} = \hat{V}_{\text{eff}} - \frac{\hat{D}_{\text{eff}}}{n} \frac{\partial n}{\partial r} = \hat{V}_{\text{eff}} + \frac{\hat{D}_{\text{eff}}}{\lambda_n} \]

- Transport coefficients much larger than Bohm...
- Transport *neither* diffusive nor convective (fascinating problem!).

LaBombard (2000)
Garcia (2007)
TCV flux of particles gradient

TCV

Garcia (2007)
Divertor Turbulence
Statistical modelling

First, we impose shape, radial motion and draining of the filament.

Next, we follow many filaments with given statistical properties.

A time history of the filament motion can be captured in a statistical sense.

Finally, we time average the filament motion and we obtain mean profiles.

\[ N(x) = \frac{1}{\tau_w} \int_{-\infty}^{\infty} dt \int_{0}^{\infty} d\eta_0 \int_{0}^{\infty} dw \eta(x, t) P_{\eta_0}(\eta_0) P_w(w) \]

Militello NF Letters and PPCF (2016)
Insight from filaments

Need to understand filaments in order to:

- Control plasma exhaust profiles
  - Minimise erosion/impurities from first wall
  - Optimise divertor wetted area
  - Maximise the lifetime of fusion reactor

- Optimise control of plasma edge
  - Maximise energy and particle confinement
  - Control fuelling and flushing of He ‘ash’
  - Optimise heating of RF heating waves

23rd EU-US TTF Meeting, 14-09-2018
Backup slides:
Misc
Fast Cameras on MAST

MAST is ideal for visual imaging of filaments

‘Open’ tin can geometry
High edge neutral density (~$10^{18} \text{m}^{-3}$)
Tight aspect ratio
Deep, wide-field views of plasma – toroidal resolution

— MAST Photron SA1.1 camera
- Installed during M9 campaign (May-September 2013)
- Unfiltered: mainly $D_\alpha$ light
- $256 \times 160$ pixels @ 100,000 f/s
- Mid-plane data for 76 shots

— MAST-U Photron SAX2 cameras
- $256 \times 152$ pixels @ 200,000 f/s
- Two cameras for stereoscopic imaging
Image analysis GUI