EUROfusion

WPJET1-CPR(18) 18917

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Preprint of Paper to be submitted for publication in Proceeding of IEEE International Symposium on Circuits and Systems ISCAS 2018

This work has been carried out within the framework of the EUROfusion Consortium and has received funding from the Euratom research and training programme 2014-2018 under grant agreement No 633053. The views and opinions expressed herein do not necessarily reflect those of the European Commission.

A New Approach to Bolometric Tomography in Tokamaks

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***Abstract*—Bolometry provides absolute measurements of total radiation losses of a plasma discharge and it is an essential instrument for the studies related to the understanding ofthe plasma behavior at different radiative fractions. In this paper we present the first results related to the implementation of a new reconstruction method for bolometry. The method is based on the maximum likelihood statistical principle. It allows the implementation of a methodology for the evaluation of the uncertainties accompanying the reconstruction and the calculated radiated power. The method has been tested using numerically simulated distributions and also on relevant experimental JET data.**

***Keywords*—bolometry; tomographic reconstruction; maximum likelihood principle; uncertainties evaluation; radiation losses;**

I. INTRODUCTION

The power handling on the first wall is one of the major issues for the next generations of tokamaks. The operation with a detached divertor is needed for maximizing the lifetime of plasma facing components. A dissipation of ~ 95% of the total heating power by radiation will be needed, with more than 70% being emitted on closed field lines. The energy dissipation by means of plasma radiation, using various additional impurity seeding schemes, is one of the main mechanisms to be used for this purpose.

On JET the radiation is measured, spatially and temporally resolved, by means of the bolometric system [1]. The diagnostic comprises two cameras with horizontal and vertical views across the cross-section of the plasma (Fig. 1). A number of 24 chords (projection lines) are available for each view. Their geometry allows an increased spatial resolution in the divertor region. Tomographic reconstruction is currently performed with the method originally developed by Ingesson [2]. It uses a grid of pyramid local basis functions that are used for the discretization of the tomographic problem. It searches for a solution which is constant on flux surface and gently varying in the radial direction. Recently a new approach, based on deep neural network, trained on an ensemble of measurements and reconstructions obtained using the method described in [2], has been proposed [3]. In case of a successful training, able to robustly generalize the knowledge in the training data, the method has the potential of providing fast reconstructions allowing the processing of a large amount of data. The idea of using neural networks for the determination of radiated power in JET has been proposed for the first time in [4]. In this approach, besides the bolometric data, elongation and triangularity have been used as input to the neural network, since these provide useful complementary information. The method has real-time capabilities.

In the present approach, we propose to apply to bolometry a reconstruction method based on the statistical maximum likelihood (ML) principle, which has been successfully used for gamma and neutron tomography in JET [5-6]. The complementary implementation of the recently developed methodology for the numerical evaluation of the statistical properties of the reconstruction uncertainties [7] will allow estimating the error bars, when deriving the total radiated power and the power profiles from bolometry.

II. MAXIMUM LIKELIHOOD TOMOGRAPHY

In bolometry the measurements are obtained by sets of detectors looking at the plasma along different lines of sight (LOS) with different orientation (Fig.1). If the emissivity distribution is denoted by f and the measurements by g, the tomographic problem can be stated by the relation:

$$\overline{g_m} = \sum_{n=1}^{N_p} H_{mn}\overline{f_n}, \quad m = 1, \dots, N_d \tag{1}$$

where:

- $\overline{g_m}$ is the mean measured data, over all zero mean noise realizations n_g:

$$g = \bar{g} + n_g \tag{2}$$

- $\overline{f_n}$ is the expected emissivity distribution corresponding to the mean data $\overline{g_m}$
- N_p is the total number of pixels, N_d is the total number of detectors
- H_{mn} represents the elements of the so called projection matrix and they account for the amount of emission from pixel n accumulated in the detector m. The calculation of the matrix H for bolometry is described in details in [8].

Assuming that the emission is a Poisson process and g_m is a sample from a Poisson distribution, whose expected value is g, then the probability of obtaining the measurement $g=\{g_m|m=1,...,N_d\}$ if the image is $f=\{f_n|n=1,...,N_p\}$ is given by the likelihood function:

$$L(g/f) = \prod_m \frac{1}{g_k!} (\bar{g})^{g_k} \times exp(\bar{g}) \qquad (5)$$

The ML estimate is obtained by maximizing the above expression:

$$f_{ML} = argmax_f L(g/f) \qquad (6)$$

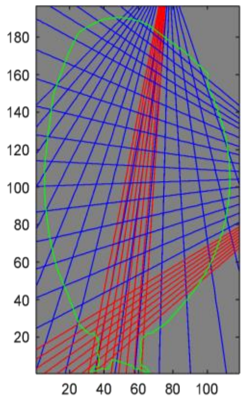

Fig. 1. Lines of sight geometry

For practical implementation an iterative solution for finding the ML estimate is the usual approach [9-10]:

$$f_n^{(k+1)} = \frac{f_n^{(k)}}{\sum_m H_{mn}} \sum_m \left(g_m / \sum_j H_{mj} f_j^{(k)} \right) H_{mn} \qquad (7)$$

where k is indexing the iterations.

The ML method incorporates also a regularizing procedure that assumes smoothness on magnetic surfaces, obtained by solving the plasma equilibrium. It is implemented as a 1-D filtering along magnetic contours.

As relation (7) is working by means of multiplicative corrections, the following change of variable is a natural option:

$$y^{(k)} = ln\left[\hat{f}^{(k)}\right] \qquad (8)$$

The measurements and the emissivity distribution are accompanied by a zero-mean noise, and therefore an expectation value:

$$E\{y^{(k)}|f\} = ln\left(a^{(k)}\right) \qquad (10)$$

and a deviation $\varepsilon(k)$ from the expectation values:

$$y^{(k)} = ln\left(a^{(k)}\right) + \varepsilon^{(k)} \qquad (11)$$

can be defined.

Two approximations can be introduced in order to derive analytical expressions for retrieving $\varepsilon(k)$ at each iterations. First, it can be considered that the noise is small in comparison with the mean reconstruction:

$$\hat{f}^{(k)} = a^{(k)} exp\left(\varepsilon^{(k)}\right) \cong a^{(k)}\left[1 + \varepsilon^{(k)}\right] \qquad (12)$$

It can be assumed also that the reconstruction algorithm is converging fast and therefore the projection of the current estimate is close to the noise free projection:

$$Ha^{(k)} \cong Hf \qquad (13)$$

Introducing these approximations in (7) and separating the noise from the signal in the resulting expression, a couple of equations can be obtained (the reader is referred to [7] for complete details):

$$f^{(k+1)} = f^k + diag\left[\hat{f}^{(k)}\right] diag\left[s^{-1}\right] \left[H^T diag\left[H\hat{f}^{(k)}\right]^{-1} g - H^T I\right) \right] \qquad (14)$$

$$\varepsilon^{(k+1)} = B^{(k)} n + \left[I - A^{(k)}\right] \varepsilon^{(k)} \qquad (15)$$

where:

$$A^{(k)} = diag\left[\hat{f}^{(k)}\right] diag\left[s^{-1}\right] H^T diag\left[H\hat{f}^{(k)}\right]^{-1} H \qquad (16)$$

$$B^{(k)} = diag\left[\hat{f}^{(k)}\right] diag\left[s^{-1}\right] H^T diag\left[H\hat{f}^{(k)}\right]^{-1} \qquad (17)$$

Equation (14) allows retrieving the reconstruction from the noise free data while equation (15) allows the retrieval of the noise accompanying the current estimate. The latter can be re-written in the form:

$$\varepsilon^{(k)} = U^{(k)} n \qquad (14)$$

where:

$$U^{(k+1)} = B^{(k)} + \left[I - A^{(k)}\right] U^{(k)} \qquad (15)$$

is an operator applied to the noise in the original data. As the noise in the measured data n_g has a normal distributions it results that $\varepsilon(k)$ will be characterized also by a normal distribution, with the covariance:

$$K_\varepsilon^{(k)} = U^{(k)} K_{n_g} \left[U^{(k)}\right]^T \qquad (16)$$

where K_{ng} is the covariance matrix for the data. Therefore the covariance of the reconstructed image is derived from the covariance matrix for the measured data by mean of the operator U.

III. RESULTS

A. *Numerical experiments*

The application of the ML method for bolometry has been tested first on a comprehensive set of phantoms. These phantoms are simulating distributions encountered in real experiments. Two representative examples are shown in Figs. 2-3. The ML provides good reconstructions in terms of shapes and resolution. Fig. 4 shows a comparison between the tomographic projections obtained, by mean of equation (1), using the phantom image and its reconstruction, respectively. It can be noticed that projections derived from the reconstruction reproduce well those resulting from the phantom.

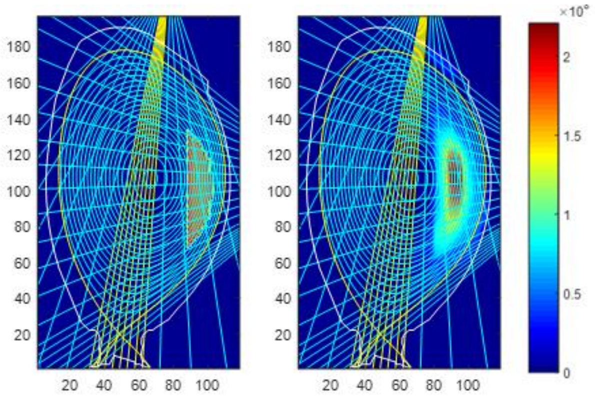

Fig. 2. Phantom mimicking a gas puffing (left) and its ML reconstruction

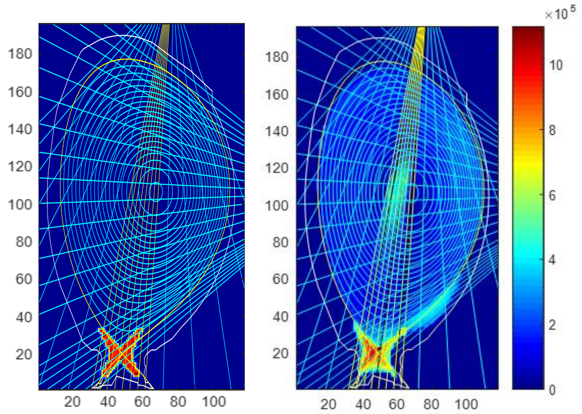

Fig. 3. Phantom showing one of the typical radiation patterns in the divertor (left) and its ML reconstruction.

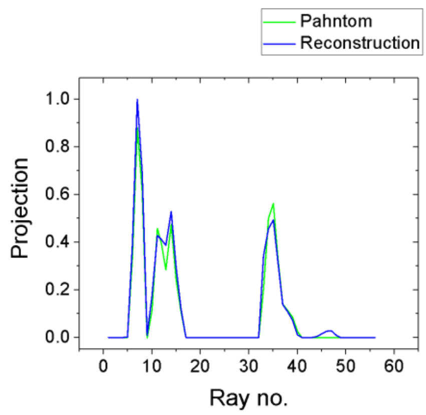

Fig. 4. Calculated projections for the phantom in Fig. 3 (green) and the back calculated projections using the ML reconstruction (blue).

As one of the main results derived from the bolometric analysis is the total radiated power, we compared also the radiation profile obtained using the phantom and its reconstruction, respectively. The radiation profile is calculated by summing the values of the image pixels located inside a certain magnetic surface. The calculation has been performed by taking into account a number of 100 magnetic surfaces. A good similarity between the two profiles is obtained, as shown in Fig. 5

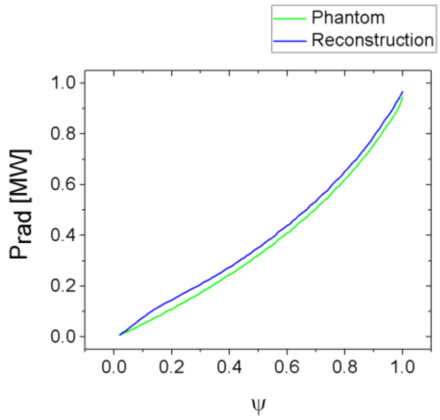

Fig. 5. Radiation profile calculated using the phantom in Fig. 3 (green) and its ML construction (blue).

B. *Experiments with real JET data*

The tests on real data have been performed mainly on measurements selected from experiments related to the investigation of radiation limiting mechanisms for various seeded impurities [11]. The future fusion power plants need to reach a level close 100% of the loss power radiated. Therefore the understanding of the mechanisms limiting the attainable radiated power fraction is very important. The evaluation of the uncertainties of the radiated power, derived from bolometric analysis, is an important ingredient for a proper physical interpretation.

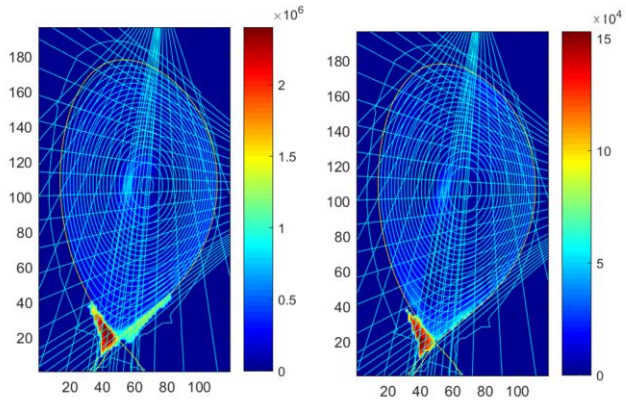

Fig. 6. ML reconstruction (left) and the corresponding variance image (right) for the JET pulse 87189 at 50.425 s.

An illustrative example is presented in Figs. 6-7. The ML reconstruction is derived by mean of (7) and its covariance matrix by using (16) and the subsequent relations as described above. The ML reconstruction is used for calculating the radiation profile while the covariance image, which describes the uncertainties of the values of each pixel in the reconstructed image can be used for calculating the error bars for the radiation profile.

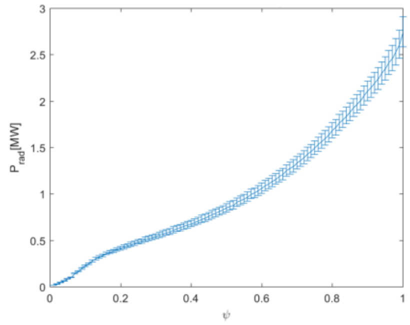

Fig. 7. Radiation profile for the JET pulse 87189 at 50.425 s. The profile is calculated using the ML reconstruction and the error bars are calculated using the variance image.

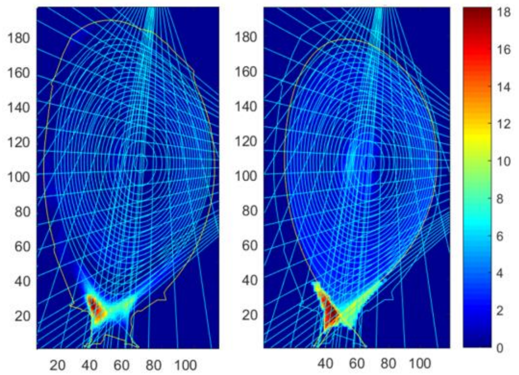

Fig. 8. Example showing a comparison between the results obtained by the ML method (right) in comparison with the method described in [2], currently used at JET.

The method has been applied also for an extensive experimental JET data set and the reconstruction have been compared with those provided by the method described in [2], which is used currently at JET for routine analysis. An illustrative example for this comparison is presented in Fig. 8. A high similarity between the two reconstructions can be noticed.

IV. Conclusion

We show in this paper that he ML method can be successfully used for bolometric tomography. The numerical tests with representative phantoms show the the method is able to provide good reconstructions in terms of shapes and resolution. This assertion is sustained also by the comparison with the method currently used routinely in JET. The main advantage of the ML method is the possibility to evaluate the uncertainties accompanying the reconstruction and the calculated radiated power.

Acknowledgment

This work has been carried out within the framework of the EUROfusion Consortium and has received funding from the Euratom research and training programme 2014-2018 under grant agreement No 633053. The views and opinions expressed herein do not necessarily reflect those of the European Commission.

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