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New Signal Processing Methods and Information Technologies for the Real Time Control of JET Reactor Relevant Plasmas

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ABSTRACT

A general trend in the experimental programmes of present day Tokamaks, and of JET in particular, is the constant increase in the number of parameters to be controlled in real time, to satisfy the machine protection requirements on the one hand and to improve performance on the other. Since the amount of data collected is also increasing at least at a rate compatible with the Moore law, significant developments are required in the field of real time algorithms particularly for magnetic reconstructions, disruption prediction and image processing. A new real time equilibrium code called EQUINOX, using internal and external measurements of the magnetic fields, has been qualified on JET. It can provide reconstructed accurate equilibria about every 50ms on a 2GHz PC. An advanced disruption predictor, based on machine learning tools, has been deployed using inputs selected with a genetic algorithm. Its success rate remains of the order of 94% for up to 170ms before the occurrence of the disruption. Nonextensive entropies, which are more sensitive to long range correlations, seem to be useful in detecting vibrations in the videos of JET cameras, both visible and infrared.

1. INTRODUCTION

To improve their reactor relevance, the configurations of present day Tokamak plasmas are very sophisticated and typically require operation at the boundary of the safe region in the parameter space, a fact that tends to make the configurations more unstable and arduous to control. These difficulties are compounded by the need to improve the compatibility of these configurations with first walls of reactor relevance (such as the ITER like wall of JET). Therefore more sophisticated solutions for real time control need to be developed and implemented.

In this respect, probably the most important line of research on JET is devoted to determining the plasma equilibrium in real time. A new code, called EQUINOX [1], is based on the solution of the traditional Grad Shafranov equation but implements a different approach with respect to traditional solutions such as EFIT [2] (see section 2).

One of the main threats to Tokamak machines is still constituted by disruptions. An advanced predictor, APODIS [3], based on an original use of Support Vector Machine methods, has been developed for JET. Recently its already very good performance has been further improved by selecting the features to be used as inputs with Genetic Algorithms [4] (see section 3).

Cameras, both infrared and visible, have become much more widespread in fusion research devices in the last decade. The image processing to be performed is quite sophisticated and requires advanced techniques. Sometimes the interpretation of the contents is made even more difficult by vibrations of the cameras. A new nonextensive entropy [5] seems to be very helpful in discriminating between the movements of objects within the frame and vibrations of the entire image (see section 4).

2. REAL TIME EQUILIBRIUM CODES

The reconstruction of the plasma equilibrium in a Tokamak is a free boundary problem in which the

plasma boundary is defined as the last closed magnetic flux surface. Inside the plasma, the equation expressing the equilibrium between the magnetic and the kinetic pressures in an axisymmetric configuration is called the Grad-Shafranov equation. This equation is derived from the combination of the magnetostatic Maxwell's equations, which are satisfied in the whole of space in presence of a magnetic field, and the plasma equilibrium, which is defined as the balance between the kinetic pressure and the Lorentz force of the magnetic pressure. The Grad-Shafranov equation is typically presented in the following form:

$$-\Delta^* \psi = rp\psi'(\psi) + \frac{1}{\mu_0 r} (ff')(\psi) \quad (1)$$

in which μ_0 is the magnetic permeability of the vacuum, $\psi(r,z)$ is the poloidal flux, $p(\psi)$ is the plasma pressure, f the diamagnetic function. Δ^* is the linear elliptic operator defined as

$$\Delta^* = \frac{\partial}{\partial r} \left(\frac{1}{\mu r} \frac{\partial}{\partial r} \right) + \frac{\partial}{\partial z} \left(\frac{1}{\mu r} \frac{\partial}{\partial r} \right) \quad (2)$$

In the right hand side of equation (1), the function $f(\psi)$ is typically not directly measured inside the plasma. On the other hand, nowadays diagnostics such as polarimetry and the Motional Stark Effect (MSE) can probe the internal magnetic fields and provide global constraints to be used in solving the Grad-Shafranov equation. Another important point to notice is that the solution to equation (2) requires in principle the modelling of all the electromagnetic structures surrounding the plasma. The solution of the general problem, including the model of the machine, provides of course more accurate results but it is very heavy in terms of computational time. In order to meet the computational requirements imposed by real-time applications, a new version of the code called Equinox has been design and implemented in C++, using a finite element method and a non linear fixed point algorithm associated to a least square optimization procedure. The code relies on tokamak specific software like XLOC [6] to provide flux values on the first wall of the vacuum vessel. By a least-square minimization of the difference between measurements and the simulated ones, the algorithm identifies the source term of the non linear Grad-Shafranov equation. In the present version of the code, the experimental measurements used are the magnetics on the vacuum vessel, the interferometric and polarimetric measurements on several chords and the motional Stark effect pitch angle measurements. For the magnetic measurements the flux loops give the poloidal flux on particular nodes M_i such that $\psi(M_i) = h_i$ on Γ . Thanks to an interpolation between the points M_i these measurements provide the Dirichlet boundary condition h . The problem is thus reduced to finding a solution that minimizes a cost function defined as:

$$J(\psi) = J_0 + K_1 J_1 + K_2 J_2 + K_3 J_3 + J_\varepsilon \quad (3)$$

with

$$J_0 = \sum_i \left(\frac{1}{r} \frac{\partial \Psi}{\partial n} (N_i) - g_i \right)^2 \quad (4)$$

$$J_1 = \sum_i \left(\int_{c_i} \frac{n_e}{r} \frac{\partial \Psi}{\partial n} dl_i - \alpha_i \right)^2 \quad (5)$$

$$J_1 = \sum_i \left(\int_{c_i} n_e dl_i - \beta_i \right)^2 \quad (6)$$

where g_i , α_i and β_i are the measurements of the magnetic poloidal field, the Faraday rotation and the line integrated density along the chords C_i respectively. The weighting parameters K_i enable to vary the importance to be given to the corresponding experimental measurements. Equations 2 and 3 are solved using a finite element method. A careful implementation leads to execution time less than 50 ms per iteration on a 2GHz PC, complemented with excellent robustness.

The version of EQUINOX using only the magnetic pickup coils as inputs has already been validated. A set of about 130 discharges, covering practically JET whole operational space, have been selected. For these shots, the estimates of EQUINOX have been compared with the equilibria provided by EFIT with good agreement. Recently also the version of the code using internal measurements has been validated. A result of an equilibrium obtained using also the measurements of the Motionl Stark Effect as constraint is shown in figure 1, confirming the quality of the EQUINOX estimates..

3. DISRUPTION PREDICTION WITH SVM AND GAS

Disruptions still affect the operation of Tokamak machines, particularly when the experiments are meant to achieve high performance. Disruptions [7] can be triggered by various instabilities which, on time scales even of the order of milliseconds, can force the plasma out of its safe operational limits with the resulting loss of energy and the termination of the plasma current. The installation of the new ITER-like wall presently under way in JET has increased the relevance of detecting an incoming disruption sufficiently in advance to have the time to undertake remedial action, such as the reduction of the plasma energy content or the injection of gas.

APODIS is a machine learning based disruption predictor explicitly conceived to operate on JET. Its architecture consists of a combination of supervised classifiers organized in two layers that allow obtaining the best disruption success rates ever achieved on JET. The first layer consists of three different predictors based on SVM. These predictors have been trained during three time intervals of 30 ms each before the disruptions. As output of these three SVM, three values are obtained. The employed Kernel in this case is a Radial Basis Function (RBF) Kernel. The second layer, implements a decision function, meant to determine whether to trigger or not an alarm based on the three previous values. It uses a linear kernel and it is trained with the output values provided by the three models of the first layer.

The feature extraction of APODIS has been recently upgraded, to determine, in an automatic way, not only the physical quantities but also their respective representations that are more appropriate to detect an incoming disruption. In the original version of APODIS, the FFT (Fast Fourier Transform) was applied to the 13 signals of table I and the standard deviation of the frequency components was used as the features to be provided as input to the SVM predictor. The new features have been obtained with Genetic Algorithms (GAs). GAs are computational methods meant to solve complex and non linear searching and optimization problems. They are inspired by the genetic processes of living organisms. In nature, individuals of a population compete for basic resources. Those individuals achieving better surviving rates have higher probabilities to attract possible partners and to generate descendants. As consequence, best adapted individuals' have higher chances to be passed on to the next generations. GAs, in order to emulate this behaviour, work with a population of individuals. Each individual represents the possible solution of a problem (for example the best set of features to identify disruptions). The quality of each individual in evolutionary terms is evaluated on the basis of a fitness function. A higher probability to have descendants is assigned to those individuals with better fitness functions. The most promising areas of the searching space are explored by favoring the crossing between the better adapted individuals. Even if the GAs do not guarantee the best solution to an optimization problem in all the cases, there is empirical evidence that proves that they provide good results in limited computational time.

In the case of the disruptions, since the objective is to improve the success rate of prediction, the role of the genes is played by the signals features. The adoption of GAs allows identifying a better set of features. GAs represent individuals as a set of bits (equivalent of genes) grouped in strings (equivalent to chromosomes). Two representations, mean values and standard deviation of the FFT of the signals, have been considered. Each bit of the string corresponds to a specific representation (for example the mean value of the plasma current or the standard deviation of the spectral components of the plasma density). A null value indicates that the feature assigned to that bit is not considered. On the contrary, a value equal to one means that this feature is taken into account (see figure 2 for an example). As fitness function, a two-class SVM classifier has been used. The value representing the fitness of an individual is the classification rate obtained with this SVM system. With the described method, it has been confirmed that the best generations converge always on almost the same signal features. The most performing generation detected so far comprises the following signals:

mean(IPLA), std(FFT(IPLA)), mean(LI_der), std(fft(LI_der)), mean(Loca),
std(fft(Loca)), mean(q95), mean(Wdia_der), mean(Dens), std(fft(Dens))

In the previous list “mean” indicates the average amplitude of the corresponding quantity over the 30ms window and “std” the standard deviation of the FFT over the same interval. In Fig.3 the success rates of APODIS have been expressed in terms of the “warning times”, which is the time difference between the disruption time and the alarm time. Each point in the curves plotted is the accumulated percentage of recognized disruptions with a warning time equal or higher than the one

specified in the corresponding logarithmic x-axis. The various predictors have been trained with examples of the campaigns 15 up to 18 and the reported results have been obtained using the test set consisting of all the disruptions of campaign 19.

It can be observed that the JET present disruption predictor JPS [8] detects, with a 0.1 second time margin, only 30 % of the 81 disruptive discharges. For the same warning times, the previous version of APODIS identifies less than 70% of the disruptions. Finally, the new version of the APODIS system recognizes 94% of the disruptions up to almost 170 ms in advance, when it is trained with the features extracted with the procedure described previously.

4. IMAGE PROCESSING

The number of cameras, both visible and infrared, operational on JET has increased significantly in the last years. About 15 additional ones are planned to be deployed in the next set of campaigns with the ITER like wall. In general these cameras can produce a very high amount of data, even several Gbytes per shot. In the last years, several image analysis methods have been explored to increase the efficiency of the data analysis [9]. Various techniques have been successfully tested to detect in an automatic way hot spots, MARFEs and even UFOs. In this paper a potential solution affecting some of JET cameras is discussed. New computational approaches, such as Cellular Nonlinear Networks, and emerging technologies, such as FPGA, have already been successfully tested [10]. The interpretation of the videos of Tokamak cameras are complicated by various aspects, ranging from the variety of time scales involved to the strong changes in the background illumination. The specific problem preliminarily addressed in this paper is the issue of vibrations. In case of big ELMs or disruptions, the supports of the cameras can vibrate affecting the images. Typically it is not possible to automatically reset the image using reference points in the frames, since the background illumination due to the plasma change too much not only from shot to shot but also within the same discharge and therefore no reference points are always available. One idea being tested at the moment consists of calculating a new type of nonextensive entropy, also called Tsallis entropy, to assess whether it can discriminate vibrations of the entire frames from the case of objects moving within the frames. The general definition of this nonextensive entropy is

$$S_{q0} = K \frac{1 - \sum (p_i)^q}{q-1} \quad (7)$$

Where p_i are the probabilities of the i pixel value in our case. If the parameter q is set to 1, the Tsallis entropy reduces to the traditional definition of the entropy. The most important aspect of the Tsallis entropy in our context is the fact that the quantity in equation (7) is more sensitive to long range correlations than the usual definition of entropy. Therefore the main idea behind this approach is to calculate the difference of subsequent frames and calculate the nonextensive entropy of the difference. If the camera is affected by any form of global movement, the difference image should present much longer correlations than the case in which a simple object moves within the

image. An example of the discriminating power of the Tsallis entropy is shown in figure 4. The nonextensive entropy with $q=0.1$ is much more sensitive to vibrations and seems to be able to discriminate whether camera movements occur. These results are encouraging but preliminary and will have to be confirmed on a wider statistical basis.

5. FUTURE TRENDS

Even if significant progress has been made in the last years in the field of data analysis for control, more needs to be done in the near future. With regard to the equilibrium reconstructions, new experimental solutions, such as ergodic divertors and ELMs mitigation strategies, introduce toroidally asymmetric components of the magnetic field, which complicate the problem significantly. The same experimental solutions also tend to increase the probability of disruptions and the difficulty of their predictions. With regard to image processing, the reactor relevant materials being more delicate than the present ones, more sophisticated real time image processing will also be required.

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Signal name	Units
1. Plasma current.	A
2. Poloidal beta.	
3. Poloidal beta time derivative.	s^{-1}
4. Mode lock amplitude.	T
5. Safety factor at 95% of minor radius.	
6. Safety factor at 95% of minor radius time derivative.	s^{-1}
7. Total input power.	W
8. Plasma internal inductance.	
9. Plasma internal inductance time derivative.	s^{-1}
10. Plasma vertical centroid position.	m
11. Plasma density.	m^{-3}
12. Stored diamagnetic energy time derivative.	W
13. Net power (total input power minus total radiated power).	W

Table 1: The 13 signals used as inputs to the APODIS predictor.

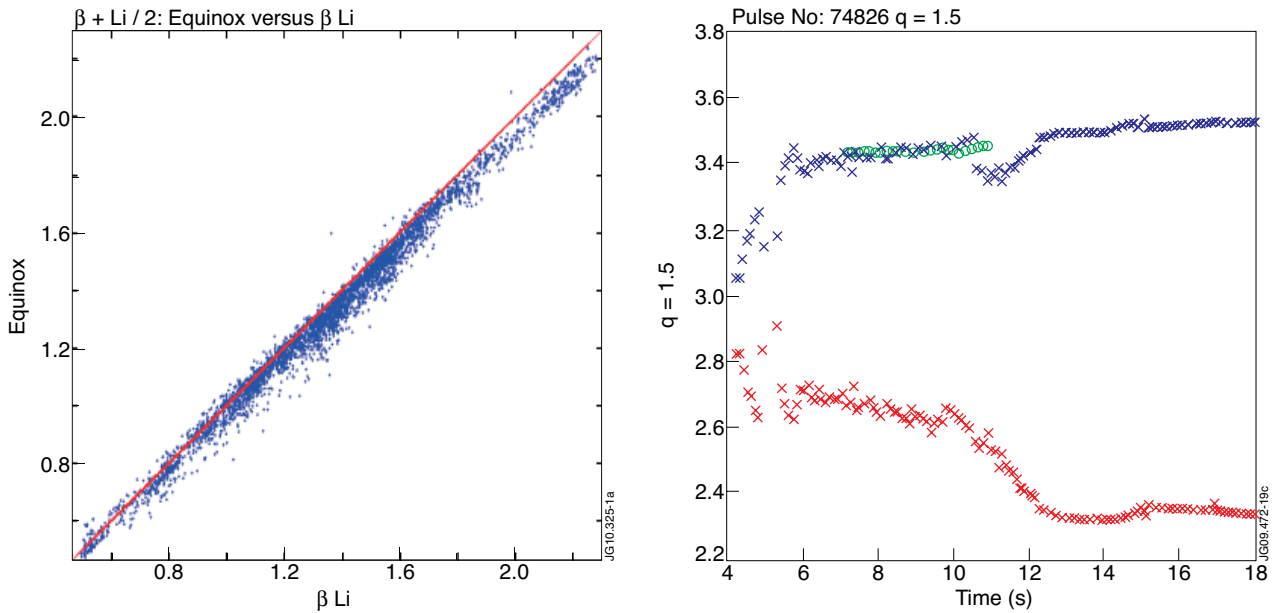


Figure 1: EQUINOX results with internal MSE measurements. Top: Shafranov shift compared with the traditional BetaLi [11] code for the entire database. Bottom: time evolution of the $q=1.5$ surface for a discharge (Pulse No: 74826) presenting MHD activity. The location of the $q=1.5$ mode is given by Equinox (cross) and identified from Fourier analysis (circles) of the magnetic measurements and electron temperature (Electron Cyclotron Emission).

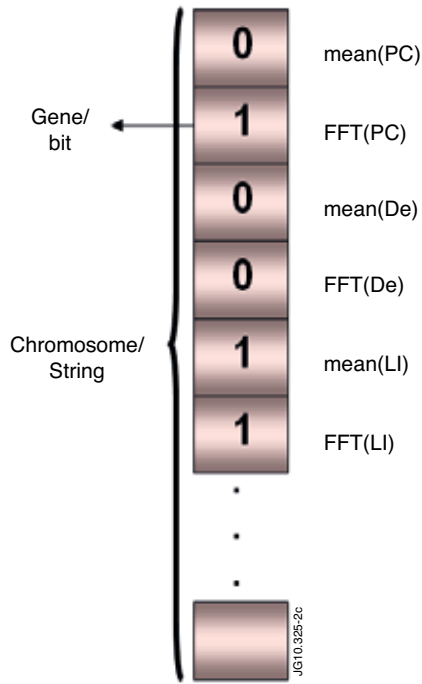


Figure 2: Example of a random individual. Values equals to 1 indicates the selection of the corresponding feature.

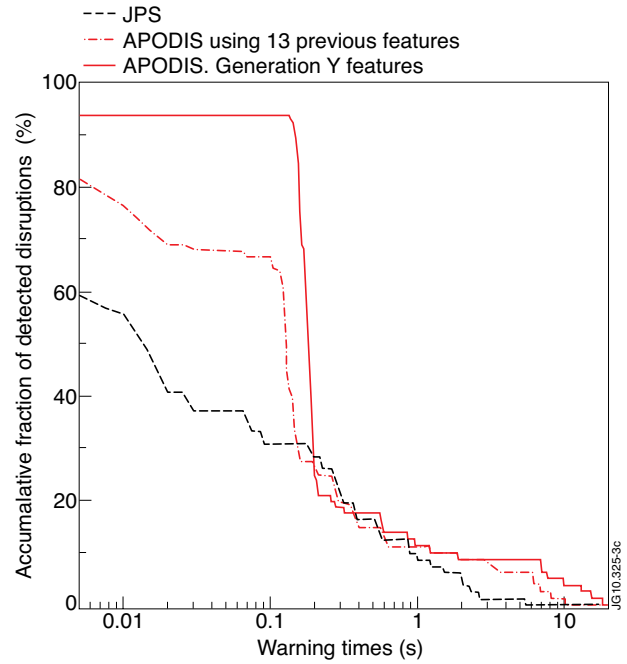


Figure 3: Performances of JPS, APODIS (previous version) and APODIS using the features selected with GAs.

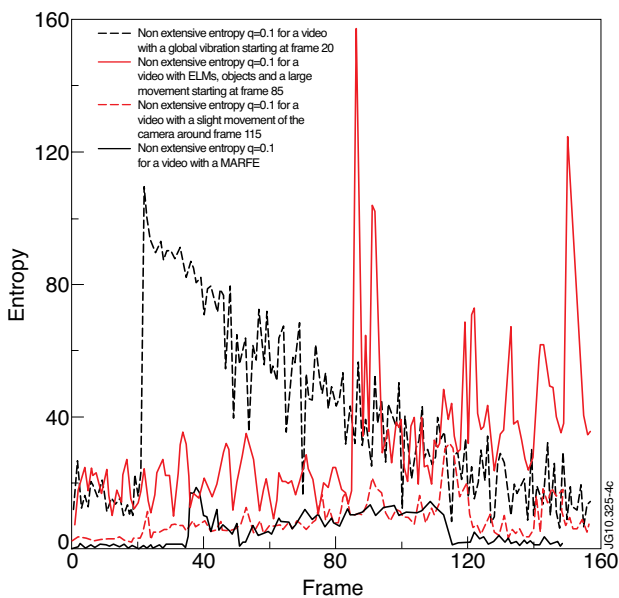


Figure 4 : Entropy of the difference of subsequent frames using the nonextensive entropy with $q=0.1$ for various types of videos. The frames with vibrations have a clearly different nonextensive entropy.