PROCEEDINGS OF SCIENCE

Advanced Disruption Predictor Based on the Locked Mode signal: Application to JET

J. Vega[1]
EUROfusion Consortium, JET, Culham Science Centre, Abingdon, OX14 3DB, UK
Laboratorio Nacional de Fusión, CIEMAT
Avenida Complutense 40, 28040 Madrid, Spain
E-mail: `jesus.vega@ciemat.es`

R. Moreno
Laboratorio Nacional de Fusión, CIEMAT
Avenida Complutense 40, 28040 Madrid, Spain

A. Pereira
Laboratorio Nacional de Fusión, CIEMAT
Avenida Complutense 40, 28040 Madrid, Spain

S. Dormido-Canto
Departamento de Informática y Automática, UNED
Calle Juan del Rosal 16, 28040 Madrid, Spain

A. Murari
Consorzio RFX (CNR, ENEA, INFN, Universitá di Padova, Acciaierie Venete SpA)
Corso Stati Uniti 4, 35127 Padova. Italy

JET Contributors
See the Appendix of F. Romanelli et al., Proceedings of the 25th IAEA Fusion Energy Conference 2014, Saint Petersburg, Russia

This article shows the development of a diagnostic tool that implements a new kind of disruption predictor. The new disruption predictor neither depends on data from past discharges nor is based on threshold amplitude. It is based on detecting anomalies in the data flow. In JET, with only the locked mode signal, the new predictor outperforms existing predictors.

First EPs Conference on Plasma Diagnostics - 1st ECPD
14-17 April 2015,
Villa Mondragone , Frascati (Rome) Italy

[1]Speaker

PoS(ECPD2015)028

1. Introduction

When macroscopic instabilities start locking to the wall, the amplitude of the signal used to detect them (called locked mode) grows during the slowing down of their rotation. Therefore, the locked mode amplitude (http://users.euro-fusion.org/pages/mags/equilibrium/eq-coil-loop/saddle-loop/saddle-loop.htm) is routinely used as precursor of disruptions caused by this locking of instabilities to the wall. However, predictors based on general machine learning methods (Support Vector Machines or Venn predictors among others) have shown better results (in terms of success rate and warning times) than simple predictions based on crossing a threshold of the locked mode amplitude. For example, in JET, the Advanced Predictor Of DISruptions (APODIS) outperforms the prediction capability of the locked mode predictor (LMP) based on a threshold criterion [1]. During the JET ITER-like wall (ILW) campaigns (September 2011 – October 2014), the APODIS success rate and average warning time are about 82% and 274 ms respectively. The equivalent quantities for the LMP are 67% and 255 ms. The reason for this difference is the exhaustive APODIS training process (almost 10000 discharges of JET with C wall between April 2007 and October 2009). APODIS is in operation with the JET ILW and, so far, no re-training has been necessary. But collecting these huge training datasets is not a realistic strategy in the next generation of experiments such as ITER.

Trying to avoid the use of huge amount of discharges in the training process, a recent alternative has been the development of disruption predictors from scratch [2, 3]. These are high learning rate predictors whose learning process starts with the first disruption. They are retrained after each missed alarm by adding disruptive and non-disruptive examples to the existing training dataset. In JET with the ILW, these adaptive predictors show success rates about 83% and average warning times of 244 ms.

A more advanced option for disruption prediction would be the use of intelligent predictors that start their learning process with each new discharge and without the need of previous information from past discharges. This article describes a disruption predictor based on a locked mode signal that does not need previous shots for training purposes. The predictor is based on the automatic recognition of changes (anomaly detections) in data streams through the identification of outliers in the data flow. Due to this reason, the predictor is called Predictor Based on Outlier Detection (PBOD). In PBOD, the locked mode samples are processed in time windows 32 ms long and these values form the data flow to be sequentially analysed. Near a disruption, the data generating model changes as the data are streamed and this change is detected and used to trigger an alarm.

Section 2 explains the concepts of anomaly detection applied to disruptions. Section 3 describes the foundations of the new predictor and section 4 shows the results in JET.

2. On-line learning and anomaly detection

In an on-line data streaming setting, data are observed sequentially and a decision on the identification of any kind of change in the data has to be made '*on-the-fly*'. Any anomaly in the data may convey interesting time-dependent information about the data. Focusing the attention on disruption prediction, the anomaly detector system has to learn in each new discharge the evolution of a safe behaviour. It is important to note that the production of discharges under different scenarios can generate different classes of non-disruptive plasmas. Therefore, in principle, the safe evolutions have to be learnt in every discharge.

An essential point in the application of anomaly detection to recognize a forthcoming disruption is to be sure that the change in the data corresponds to the identification of a disruptive event. Otherwise, lots of false alarms would be triggered and the production of interesting plasma scenarios would be impossible. A single quantity closely related to disruptions is the locked mode amplitude. Therefore, in a first approach, this signal will be the only one used for the implementation of a disruption predictor based on anomaly detection.

At this point, it is necessary to mention the requirements to be met by a disruption predictor based on anomaly detection. First, it is important to note that the sequential data are read only once. Second, the delay between a true alarm and its detection has to be minimal. Third, it should be noted that the number of both missed alarms and false alarms must be minimal. Last but not least, data streams should be handled efficiently from a computational point of view, which is crucial for the real-time implementation of the predictor.

3. PBOD foundations

There are two main factors in the development of the PBOD predictor: the disruption recognition criterion and the temporal resolution of the predictions. The first one is the key of the method to maintain low rates of false alarms, low rates of missed alarms, low rates of premature alarms (in JET, warning times greater than 1.5 s), low rates of tardy detections (in JET, warning times less than 10 ms) and high rates of valid alarms (in JET, warning times between 10 ms and 1.5 s). The second factor plays a central role to trigger an alarm as soon as possible and, therefore, to achieve the largest possible warning times.

It should be noted that PBOD has to perform better than the standard predictor based only on triggering an alarm when the locked mode amplitude crosses a threshold. Following the experience for feature selection in [1, 2, 3], PBOD also uses time windows to extract relevant information for the predictor. The locked mode signal is sampled at 1 kSamples/s (same sampling rate than APODIS) and the basic time window is 32 ms long (again the same temporal length used in the APODIS windows). This means that there are 32 samples to process in every 32 ms long time window. The information contained in these 32 samples is compressed into a reduced number of components by means of the Haar wavelet transform (approximation coefficients). The wavelet transform allows retaining both the time and the frequency information of the signal. Each decomposition level of the Haar transform reduces a factor of 2 the number of points in the initial signal. Therefore, the application of the Haar transform at decomposition levels 1, 2, 3 and 4 compresses the information into 16, 8, 4 and 2 samples respectively.

With regard to the temporal resolution, 32 ms is too long. A resolution of 2 ms is a reasonable choice. However, to avoid increasing the sampling rate, a window sliding mechanism is used. This means that after processing (Haar transform) the first time window (samples 1-32), the second time window is made up of samples 3-34, the third one contains the samples 5-36 and so on. In other words, every 2 ms, the latest 32 samples are processed with the Haar wavelet transform.

Fig. 1(a) shows a scatterplot of the locked mode signal in the bi-dimensional space defined by the Haar transform at level 4 of decomposition. It corresponds to a non-disruptive discharge.

Points are plotted every 2 ms by applying the sliding window mechanism described above. The points in this bi-dimensional space show a compact cluster structure. Fig. 1(b) is the corresponding scatterplot of a disruptive shot. It is clear that the data points are grouped in the non-disruptive phase of the discharge but they start to be '*far away*' from the cluster centre when the disruption is approaching. According to this, the red point is the first outlier in the data flow and its recognition determines when to trigger an alarm.

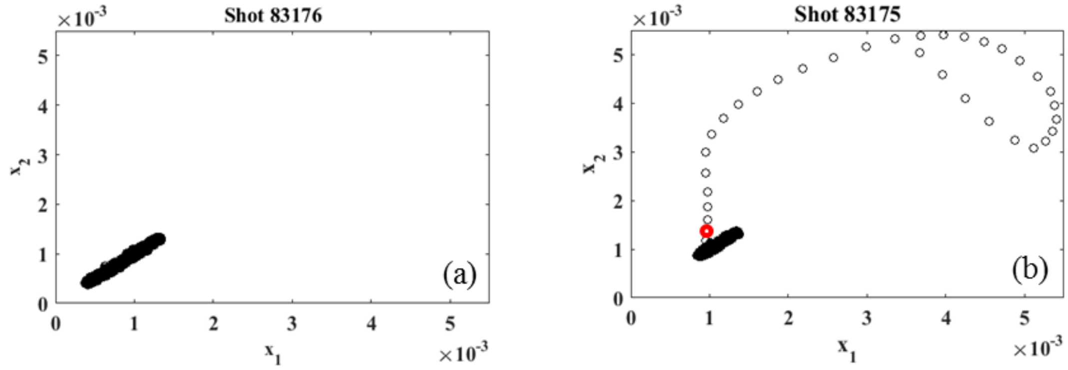

Fig. 1: Scatterplots with same scales for a non-disruptive discharge and a disruptive one. The data dispersion is much larger close to a disruption. (a) Compact cluster. (b) The presence of outliers is related to a forthcoming disruption.

As it has been pointed out, the red point in fig. 1(b) is the first point that is '*far enough*' from the cluster centre. A simple inspection of fig. 1 shows a positive covariance in the data, which is the general trend in all JET discharges. Therefore, a Euclidean metric cannot be used to determine when a point is '*outside*' the cluster. This is a consequence of the lack of circular symmetry in the cluster and its use would imply the triggering of lots of false alarms. Instead, the Mahalanobis metric does adjust for covariance according to the following equation: $D_{ij}^2 = \left(\mathbf{x}_i - \mathbf{x}_j\right)^T \Sigma^{-1} \left(\mathbf{x}_i - \mathbf{x}_j\right)$, where Σ^{-1} is the population covariance matrix of the data matrix $\mathbf{X}$. This means that typically, the isodistance contour with the Mahalanobis metric is not a circle but an ellipse (fig. 2). Therefore, this kind of distance results a proper option to identify outliers in the bi-dimensional space of fig. 1.

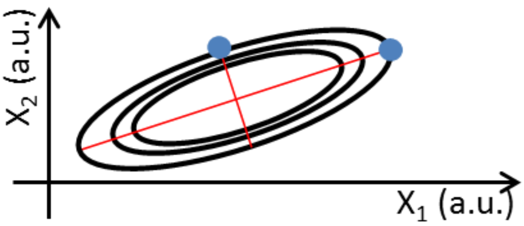

Fig. 2: Simple example in a bi-dimensional space. The isodistance contours are ellipses. Therefore, the blue points have the same Mahalanobis distance to the centre.

Fig. 3 shows the temporal evolution of the Mahalanobis distance of each new data point (with a temporal resolution of 2 ms) in relation to the cluster centre formed by all previous data points in the respective discharges. However, determining a threshold in the Mahalanobis distance to trigger an alarm can be dependent on the type of plasma scenario. Therefore, to avoid this, the criterion to identify outliers at a time t_p will be related to Mahalanobis distances greater than K_M standard deviations from the baseline model of each discharge (fig. 3):

$$\left| \frac{D_{Mahalanobis}(t_P) - mean\left(D_{Mahalanobis}(t \le t_P)\right)}{std\left(D_{Mahalanobis}(t \le t_P)\right)} \right| \ge K_M . \qquad (1)$$

In this PBOD first version, K_M has been set empirically to a value of 10, which provides slightly better results for JET. At present, it is unknown if this value will be the same for other tokamaks. On the other hand, it should be emphasized that research is needed to determine the value '*on-the-fly*' in each discharge.

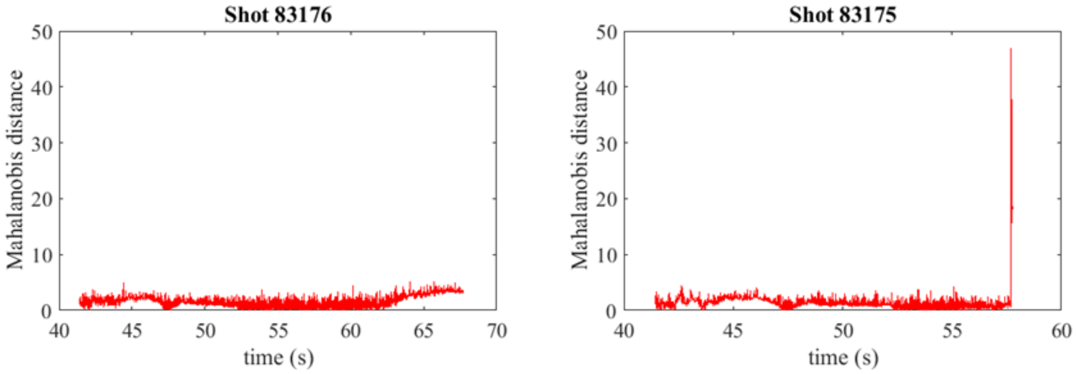

Fig. 3: Temporal evolution of the Mahalanobis distance in safe and disruptive discharges. The large increase at the end of discharge 83175 identifies outliers.

Fig. 4(a) shows the temporal evolution of both the locked mode signal (top plot) and the outlier factor from eq. (1) (bottom plot) for discharge 83175. PBOD triggers the alarm with greater warning time than both JET LMP and APODIS predictors. Fig. 4(b) is a different discharge in which the LMP predictor missed the alarm but PBOD recognizes the disruptive behaviour with a warning time of 166 ms.

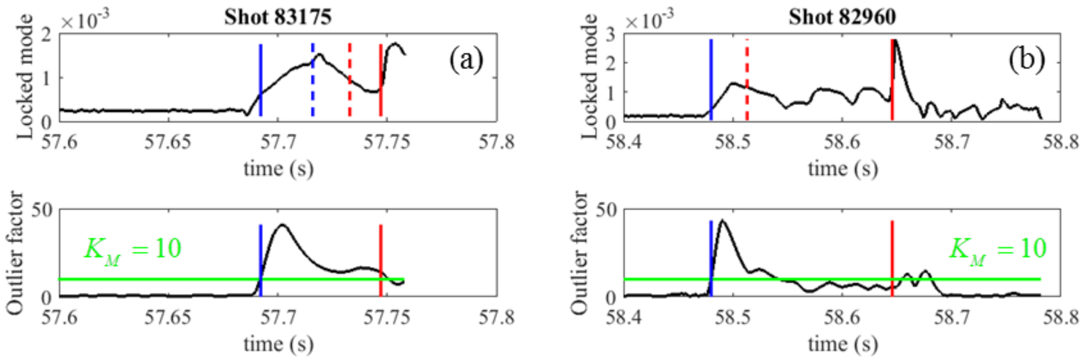

Fig. 4: Red plain lines: disruption times. Red dashed lines: APODIS prediction. Blue dashed lines: LMP predictions. Blue plain lines: PBOD predictions.

4. Results

PBOD has been applied in JET to all unintentional disruptions (566 discharges) and all non-disruptive discharges (1738) in the range 82460-87918 (ILW experimental campaigns). Table 1 shows the results. The first column represents the number of remaining components in each time window after applying the Haar wavelet transform. The other columns are the rates that have been defined in section 3. Except in the case of compressing the information to 16 data points, all other predictors are quite similar and show very promising results. Our interpretation about the case of 16 points per window is the lack of enough compression in the feature space.

Table 1: PBOD results with different data compression after the Haar transform

Data compression	False alarms (%)	Missed alarms (%)	Tardy detections (%)	Valid alarms (%)	Premature alarms (%)
2	7.13	13.43	3.53	81.45	1.59
4	7.31	11.48	3.36	83.22	1.94
8	7.42	11.84	3.00	83.39	1.77
16	+18	12.37	3.71	81.80	2.12

Figure 5 summarizes and compares the results of LMP, APODIS and PBOD for the above set of discharges. The average warning times for the LMP, APODIS and PBOD predictors are 255, 274 and 288 ms respectively.

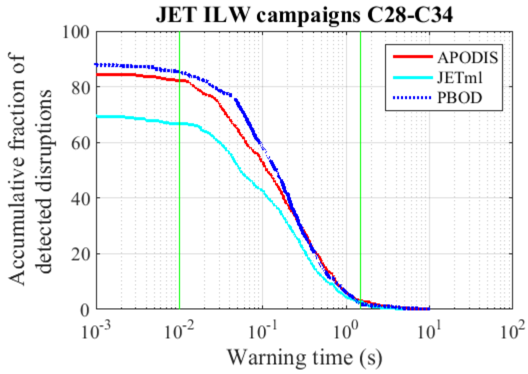

Fig. 5: Comparison between LMP, APODIS and PBOD.

Acknowledgements

This work was partially funded by the Spanish Ministry of Economy and Competitiveness under the Projects No ENE2012-38970-C04-01 and ENE2012-38970-C04-03.

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.

References

[1] J. Vega, S. Dormido-Canto, J. M. López, A. Murari, J. M. Ramírez, R. Moreno, M. Ruiz, D. Alves, R. Felton and JET-EFDA Contributors. "Results of the JET real-time disruption predictor in the ITER-like wall campaigns". Fusion Engineering and Design 88 (2013) 1228-1231.

[2] S. Dormido-Canto, J. Vega, J. M. Ramírez, A. Murari, R. Moreno, J. M. López, A. Pereira and JET-EFDA Contributors. "Development of an efficient real-time disruption predictor from scratch on JET and implications for ITER". Nuclear Fusion. 53 (2013) 113001 (8pp).

[3] J. Vega, A. Murari, S. Dormido-Canto, R. Moreno, A. Pereira, A. Acero and JET-EFDA Contributors. "Adaptive high learning rate probabilistic disruption predictors from scratch for the next generation of tokamaks". Nuclear Fusion. 54 (2014) 123001 (17pp).