Machine learning approach for operational phases identification in H-mode Density Limit disruptions

M. Lacquaniti[1], G. Sias[1], B. Cannas[1], A. Fanni[1], M. Maraschek[2], A. Gude[2] and the EUROfusion MST1 Team*

[1] *Electrical and Electronic Engineering Dept.-University of Cagliari, Cagliari, Italy.*

[4] *Max-Planck-Institut für Plasmaphysik, Garching bei München, Germany*

* *See Labit et al 2019 (https://doi.org/10.1088/1741-4326/ab2211) for the EUROfusion MST1 team.*

Abstract

This paper proposes a manifold learning method for the automatic identification of the H-mode degrading and breakdown phases, and the MARFE occurrence for H-mode density limit disruptions at ASDEX Upgrade. The potentiality of the isometric feature mapping (ISOMAP) in dimensionality reduction has been exploited to achieve the 3D mapping of the high dimension operational space. The projection of test samples into the ISOMAP allows the monitoring of the H-mode density limit disruption through its characteristic phases and events making possible the automatic detection of their occurrence.

Introduction

At present days, the prediction of disruptions can be addressed to provide an alarm sufficiently far in advance to apply either effective disruption avoidance for discharge maintenance, or mitigation actions for preventing the machine to be damaged. Each type of disruption follows a sequence of events, i.e., its own path, until the discharge disrupts. Such path will serve as the physics basis for early disruption handling. This paper focuses on the detection of the key phases on disruptions provoked at ASDEX Upgrade by forcing a density limit in H-mode. In [1], four distinct operational phases are identified in H-mode density limit: stable H-mode, degrading H-mode, H-mode breakdown, L-mode. In [2], a 2D plasma-state boundary is proposed to detect the break-down of the H-mode as an early sensor for avoiding H-mode density limit (HDL) disruptions and recovering them to full performance. Furthermore, in HDL disruptions the plasma is strongly cooled from the edge and this is typically accompanied by a MARFE. In this paper, in view of developing an HDL disruption predictor, a Machine Learning (ML) algorithm is proposed to identify the starting of the degrading and breakdown phases and the MARFE formation in the X-point region. Among ML algorithms, an unsupervised nonlinear dimensionality reduction algorithm, the ISOMAP [3], has been investigated to map the high-dimensional operational space of the AUG - HDL disruptions into a 3D map. By projecting a test pulse into the ISOMAP it is possible to track its evolution throughout the characteristic HDL chain of events. In particular, a criterion is proposed to automatically detect the beginning of the H-mode degrading and breakdown phases (t_{DG} and t_{BD} respectively) and the MARFE formation time (t_M).

Database

The considered database consists of 26 disruptions coming from HDL dedicate experiments performed at AUG from 2011 to 2016. For each disruption, t_{DG}, t_{BD} and t_M were manually identified. In this work, the data are featured by 14 plasma parameters: safety factor, internal inductance, plasma energy, feed forward gas puff rate, electron density from a peripheral DCN interferometer line of sight, Greenwald fraction, total input power. Moreover, to include the spatiotemporal information held by the plasma profiles, the mean value of the radiated power, from the foil bolometer horizontal camera, has been evaluated over the whole cords and among the upper, the core and the divertor chords separately. Finally, the electron temperature mean value from the ECE radiometer over inner, intermediate and outer channels have been included.

Method and discussion

The ISOMAP is a nonlinear technique that performs dimensionality reduction preserving the geodesic distance in a lower dimension. The geodesic distance matrix is estimated by first constructing a graph with Euclidean distances between neighbour points as edge weights, and then approximating the geodesic distance between all pairs of points by measuring the shortest path distance on the graph. Through eigenvalue decomposition of the geodesic distance matrix, the low dimensional embedding of the dataset can be attained. In this work, for sake of visualization, the mapping is displayed visualizing the three most relevant principal components (a_1, a_2, a_3). Figure 1, lefts side, reports the 3D ISOMAP for the 14D HDL operational space defined by 20 pulses, where the samples has been coloured depending on their membership to the different phases. The phase from the flat-top of the plasma current beginning until the t_{DG} is labelled as “stable” and coloured in green. The degrading of H-mode is orange, and the phase from t_{BD} to the disruption time (t_D) is red (labelled as breakdown). Instead, figure 1, right side, reports the 3D ISOMAP for the 14D HDL operational space defined by 17 pulses, where the colours identify the phase before (cyan) and after (magenta) the MARFE occurrence. Note that, the ISOMAP is an unsupervised algorithm, thus the information about the sample membership is not exploited during the algorithm training, it is just added to the low-dimensional display. For both mapping, the colouring highlights as the different HDL phases are quite separated.

This paper proposes a best matching method to project into the ISOMAP test samples, thus not

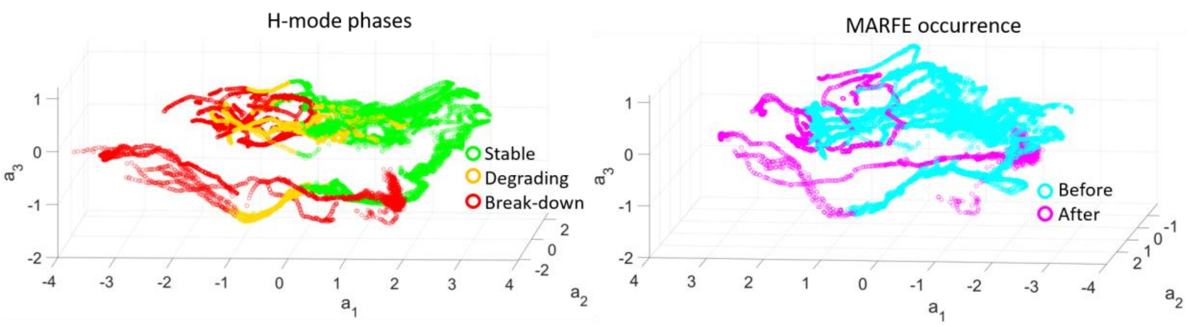


Figure 1: 3D ISOMAP for the 14D HDL operational space. Left side, the samples has been coloured depending on their membership to the different phases: stable (green), degrading (orange) and breakdown (red). Right side, the colours identify the phase before (cyan) and after (magenta) the MARFE occurrence.

belonging to the graph built during the ISOMAP training, in order to track the pulse evolution throughout the several HDL phases. As an example, Figure 2 left sides, shows the projection of the test pulse #33680 (in grey) on 2D MARFE-ISOMAP (plane a_1, a_2). The shade from light grey to black indicates the geodesic distance reduction of the samples from the closest MARFE. It has been noted that the pulse trajectory starts in the region free from MARFE (light grey), then reaches a region populated by MARFE affected samples, where geodesic distance falls down (black), and finally evolves progressively increasing the geodesic distance again (grey). The evolution of the pulse into the map suggests to use the ISOMAP for automatically identifying the MARFE formation time t_M. Moreover, the same rationale can be implemented for identifying t_{DG} and t_{BD}, allowing us to plan avoidance actions reliably before the disruption occurrence. To this purpose, a function has been defined which provides the dissimilarity of each sample to the stating points t_{DG}, t_{BD} and t_M represented in the mapping. When a test sample is projected into the map, the average of geodesic distance of its k neighbours from the starting points is evaluated, then the minimum average is assumed as the dissimilarity measure from the considered event. Figure 2, right side, reports the dissimilarity function (black line) from the MARFE occurrence for the test pulse #33680, and its minimum value match with the manually identified t_M (red line). Therefore, for each staring time, an alarm criterion has been optimized based on a dissimilarity threshold value and a dissimilarity function time derivative. In particular, an alarm is triggered when the dissimilarity measure falls underneath an optimized threshold, or the dissimilarity function decreases faster than a speed limit. Figure 3 reports the difference between the automatically identified times and the manual detected ones ($\Delta t = t_{auto} - t_{manual}$), both for training (red circle) and test pulses (black circle). From the top to the bottom, the subplot refers to t_{DG}, t_{BD} and t_M automatic detection. In each subplot, the horizontal dashed black lines report the shortest length, observed in the training set, of the phase following its own starting time. Six shots have been used as test for detecting t_{DG}, t_{BD}, and 9 shots for detecting

t_M, for 2 of which no MARFE occurrence was manually detected. With the proposed method, no false Alarms were triggered for MARFE events, and only one starting event is missed for the degrading H-mode phase.

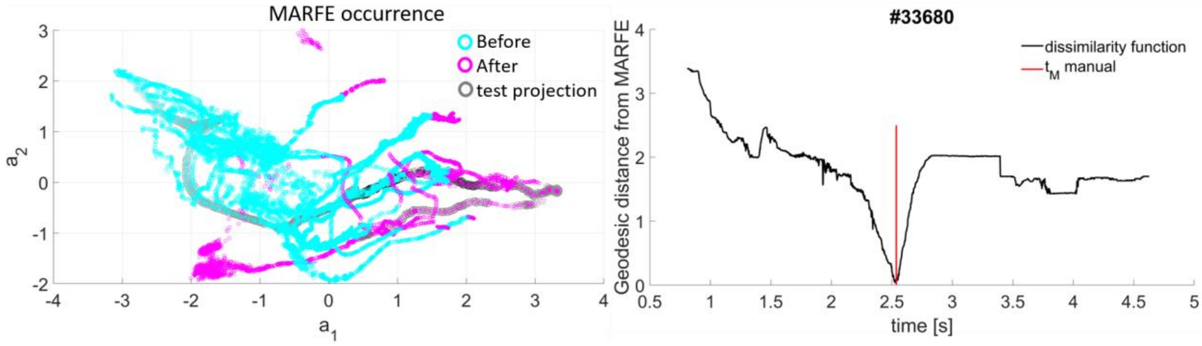
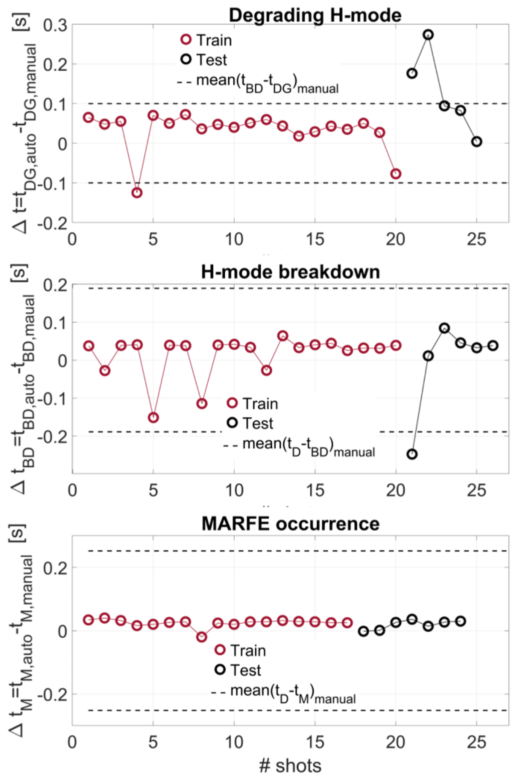


Figure 2. Left side: projection of the test pulse #33680 into the MARFE-ISOMAP (plane a1, a2), the shade from light grey to black indicate the geodesic distance reduction of the samples from the closest MARFE. Right side: dissimilarity function from the MARFE occurrence (black line), manually identified MARFE time (red line).



Conclusion

The proposed ML method allows the automatic detection of the staring time, with deviations from the manually identified times, within 273 ms for the degrading H-mode phase, 248 ms for the H-mode breakdown and 36 ms for the MARFE occurrence. One degrading H-mode starting time is missed, and no false alarms were triggered for MARFE events. A larger database is under construction to improve method generalization capability and to test false alarms on no HDL disruptions.

Figure 3. Difference between the automatically identified times and the manual detected ones for training (red circle) and test set (black circle) for the different HDL events.

Acknowledgement

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 and 2019-2020 under grant agreement N° 633053. The views and opinions expressed herein do not necessarily reflect those of the European Commission.

References

[1] M Bernert, *et al.*, *Plasma Phys. Control. Fusion* 57 (2015) 014038

[2] M Maraschek, *et al.*, *Plasma Phys. Control. Fusion* 60 (2018) 014047

[3] Sam T. Roweis and Lawrence K. Saul, *Science* 22 (2000) Vol 290, Issue 5500