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An Automatic Identifier of Confinement Regimes at JET combining Fuzzy Logic and Classification Trees

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Abstract. In modern thermonuclear fusion devices it is possible to distinguish distinct types of plasma confinement regimes which have different performance in terms of confinement time. Discriminating among them could represent a useful feature for an efficient control of a plasma experiment. An automatic identifier based on fuzzy logic is here proposed together with an unsupervised technique, using classification and regression trees, for selecting, among several diagnostic signals available, the inputs to be provided to the identifier.

1 Introduction

The necessity of reducing the greenhouse gases emission, together with the increasing energy requirements and the expected shortfalls in fossil fuels, pushed the research of alternative energy sources. Among them nuclear fusion, that is the process whereby the nuclei of two atoms fuse together forming an heavier nucleus and energy as a by-product, although not commercially available and still technologically challenging, represents an appealing solution.

Nowadays the most promising strategy to achieve nuclear fusion is thermonuclear fusion, which consists of heating the particles of a plasma to sufficiently high temperatures to overcome the electrostatic repulsion of the positive nuclei, in magnetic confinement fusion plants like tokamaks or stellarators. In the last decades, researchers have exerted great efforts to achieve the final goal of a self sustained plasma. Although this has not been accomplished yet, significant improvements in plasma control and confinement were obtained together with a relevant increase in the knowledge of the physics underlying the plasma magnetic confinement.

Among them, the discovery of the so-called H-mode of confinement in ASDEX (Axially Symmetric Divertor EXperiment) Upgrade [1] is particularly relevant. It was observed that under certain conditions of additional heating, there was an abrupt transition to an improved confinement mode. The H-mode of confinement is characterized by a sharp temperature gradient near the edge (resulting in an edge "temperature pedestal") and about a 100% increase in energy confinement time compared to the normal L-regime. Preserving this regime as long as possible during a plasma experiment is then desirable in order to maximize the performance. To achieve that, an adequate scenario and control strategy should be implemented. However, one of the main limitations of present day control schemes is their static nature, i.e. the fact that the plasma is assumed to reach a certain confinement state at a certain time “a priori”, on the basis of the pre-programmed discharge parameters. The actual real time control strategy is then determined on the basis of the assumption about the regime reached by the plasma at the time of the feedback. As already reported in ASDEX Upgrade [2], when unexpected variations in the plasma confinement state sometimes occur, as in all other tokamaks, the real time controller can, on certain occasions, apply a non optimal strategy which can be counterproductive, contribute to the degradation of the plasma performance and even induce disruptions.

Determining in real time (with a time scale in the order of milliseconds) and in an automatic way the confinement regime of the plasma could give the opportunity to adopt the best feedback strategy for the actual scenario and not for the one assumed a priori before the shot. However, discriminating if the plasma is in the L or H mode of confinement is not straightforward. First of all there is no single quantity providing a unique discrimination. Moreover the most useful measurement, typically used by the specialists in their off line analysis, is the Deuterium-Alpha emissions ($D\alpha$) which is difficult to analyze automatically because the relevant information cannot be reliably determined on the basis of static measures, but rather it resides in the time history and power spectrum of the signal. In order to solve this problem, several attempts were performed, trying to discriminate the regime on the basis of a series of magnetic and kinetic measurements using soft computing techniques.

The first attempt was made by Franzen et al. [2], who devised a fast online regime identification algorithm for ASDEX upgrade. Other examples are represented by Martin and Bühlmann [3] on the TCV Tokamak and Giannone et al. [4] on ASDEX upgrade.

An automatic regime identifier at Joint European Torus (JET) was devised by some of the authors in [5]. They, firstly, performed a systematic analysis of the best way to include the information of the $D\alpha$ signal since it is the main quantity used by the specialists to discriminate between H and L regime of confinement. A comparative performance assessment was then carried out comparing the results obtained by Fuzzy Logic (FL) and Support Vector Machine (SVM) on one side and

Discriminant Analysis on the other. FL and SVM approaches used as input a maximum of four quantities derived from only two diagnostic signals, the Dα and the normalized beta β_N, while a Discriminant Analysis identifier was provided with combinations of up to five diagnostic signals. While the Discriminant Analysis approach provided at best a success rate of 90%, the other two methods were able to achieve more than 95% of successful classifications, with the Fuzzy Logic outperforming the SVM when a lower number of inputs is used.

In the previous work, the choice of the variables to be provided to the FL and SVM identifier were driven by the request to include the Dα in the set of parameters describing the plasma and to minimize the dependence on the engineering parameters of the discharge using derivatives or normalized signals. In this work, instead, the authors propose a technique to automatically select, among the available diagnostic signals and derived quantities, those whose informative content is most related to the application. To this end, a feature selection analysis based on the Classification And Regression Tree (CART) [6] method was undertaken to assess the relative importance of the various signals. The most important ones were then selected as input variables for a FL based identifier, which was developed exploiting again the output of a classification tree built starting from the subset of inputs. Apart from the importance of the application in nuclear fusion research, to the best of our knowledge, it is the first time that CART method is used to support the membership function design phase in a Fuzzy network, obtaining a performance even greater than that one derived only considering the expert indications.

As regards the structure of the paper, in the next section a description of the database and of the method to select the input signals is reported. In section three the fuzzy logic based identifier is described together with some experimental results. Finally the conclusions are drawn.

2 Database and Input Signal Selection

The database was produced incorporating a large variety of conditions, in terms of plasma density, plasma current, and heating power. The chosen pulses, the same of the previous work [5], were considered by various experts of JET team to evaluate and verify the transition times. This information was used to validate the results obtained. A total of 15 signals were selected among the data available in real time from JET's diagnostics. In addition, the D_α signals of three different divertor views (inner, outer and vertical) were post processed in order to obtain parameters that could be a suitable input for the fuzzy logic identifier. In this way other nine signals were produced which are the D_α spectrum integral, the D_α continuous component and its time derivative for the three different views. A list of these plasma parameters together with their abbreviation is reported in the first column of Table 1.

In order to select among them the most suitable input signals to be used for the regime confinement mode classification and transition detection, all the signals were provided as inputs to build a classification tree. The samples classified by the experts as in L-mode were labeled with a '0' while the data classified as H-mode with a '1'.

Table 1 reports in the third column the variable ranking for the produced tree. It is possible to observe that only the first six parameters appear to contribute significantly to the classification process. Although the spectrum integral from the three different views could seem redundant, as the three signals usually have a similar trend (and can therefore be considered surrogates in the classification tree), their utilization is required, since the strike points could be distant from one of the line of sights making the corresponding signal less usable in the transition identification.

Quantity	Symbol	Importance
Beta normalized	β_N	100,00
Plasma density	Dens	84,65
Magneto-hydrodynamic energy	W_{mhd}	81,01
$D\alpha_{outer}$ spectrum integral	$D\alpha_{outer}$-SI	80,61
$D\alpha_{inner}$ spectrum integral	$D\alpha_{inner}$-SI	77,93
$D\alpha_{vertical}$ spectrum integral	$D\alpha_{vertical}$-SI	74,08
Time derivative of diamagnetic energy	FDWDT	2,80
Plasma elongation	K	2,00
$D\alpha$ emission outer divertor FOV	$D\alpha_{outer}$	1,77
$D\alpha_{inner}$ continuous component	$D\alpha_{inner}$-CC	1,73
Plasma current	Ipab	1,63
$D\alpha$ emission inner divertor FOV	$D\alpha_{inner}$	1,61
Total heating power	P_{tot}	1,18
Time derivative of normalized beta	$d\beta_N/dt$	1,07
$D\alpha_{vertical}$ continuous component	$D\alpha_{vert}$-CC	0,94
$D\alpha_{outer}$ continuous component	$D\alpha_{outer}$-CC	0,85
$D\alpha$ emission vertical divertor FOV	$D\alpha_{vert}$	0,65
Time derivative of $D\alpha_{outer}$ continuous component	$dD\alpha_{outer}$-CC/dt	0,64
Time Derivative of $D\alpha_{inner}$ continuous component	$dD\alpha_{inner}$-CC/dt	0,61
Toroidal magnetic field	B_T	0,58
Plasma inductance	LI	0,52
Safety factor	Q_{95}	0,48

Table 1: Relative importance of the various signals used as classifiers in CART.

3 Fuzzy Logic Based Regime Identification

A fuzzy system for the identification of the plasma confinement regime was developed providing as inputs the six signals identified from the CART relative importance estimation. The motivation behind the decision to adopt FL is manifold. Apart from the results obtained in [5] FL, allowing the representation of linguistic variables through fuzzy sets, is a very good tool to take into account the very valuable but often not easily quantifiable opinion of the experts. The fuzzy network can be, then, developed using both human expertise, and contribution from data, allowing to get easily into the model to modify it.

The network was developed by means of the MATLAB Fuzzy Logic Toolbox [7] using a Mamdani-type fuzzy inference system (FIS) [8]. In perfect agreement with the philosophy of FL, the output of the network, the confinement mode of the plasma, is not represented by a crisp indicator but by a continuous quantity, a number comprised between 0 and 1, 0 indicating the L-mode and 1 the H-mode, respectively.

In order to determine the membership values for each input variable and also the inference rules, the selected input variables were used to build a new classification tree. The information provided by the tree in terms of split values was used to select the memberships while the rules from each splitting node were the starting point for devising the if-then rules. A subsequent trial and error phase was performed in order to refine the fuzzy identifier. In this phase, to achieve better results especially in proximity of the transition, a feedback on the detected mode is added. The network so obtained was constituted then by 7 inputs (the 6 signals selected through CART and the mode detected in the previous time step) with 3 memberships for each variable and a total of 12 rules.

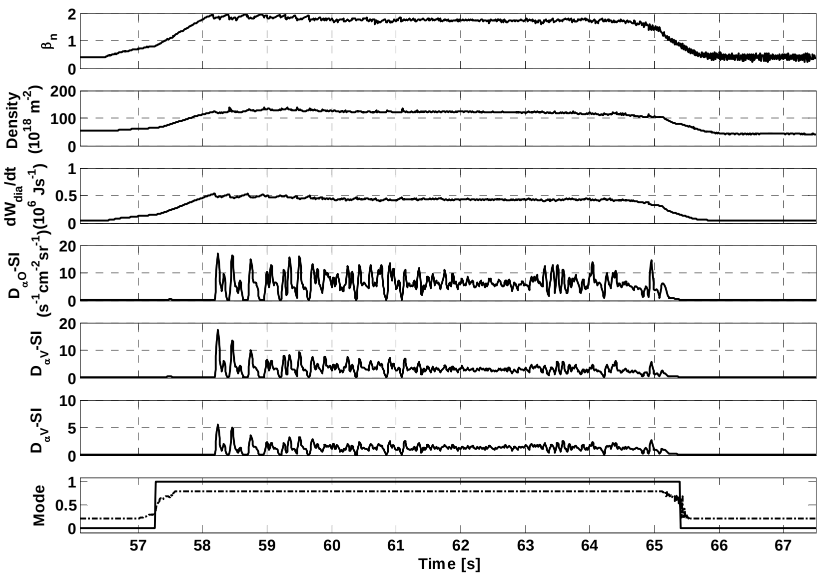

Fig. 1: Shot 58569, L to H transition time 57.26s, H to L transition time 65.4: trend of the input signals together with a comparison between the observed (i.e. from the experts) and the detected (i.e. from the classifier) confinement regime mode (0 L-mode, 1 H-mode).

The resulting fuzzy identifier was tested on the shots from the database, a total of 20, and then compared with the estimated transition times from the experts. The network was able to classify correctly the 97.7% of the cases with an improvement of about 2% compared to the previously devised network [5]. As regards the performance in proximity of the transition (the most critical part), evaluating the classification results 0.5 seconds before and after the L to H and H to L transition, the identification success goes down to the 87%, with an improvement of about 4% with respect to the old classifier. Evaluating the performance in terms of time difference with respect to the transition time identified by the experts, the L to H transition is estimated by the identifier with a mean time difference of 0.11 s while the H to L transition with a time difference of 0.18 s. An example of the output provided by the network compared with the classification supplied by the experts is depicted in Fig. 1, where is also reported the trend of the input variables.

4 Conclusions

An automatic identifier based on FL is proposed together with a CART analysis to automatically select, among several diagnostic signals available, the relevant inputs to be provided to the identifier. The outputs of the CART analysis were also the basis for the membership selection and rule design of the fuzzy identifier.

The devised network reaches a success rate of about 97.7%, providing an improvement of 2% compared to the previous network, designed considering only the information from the experts, both for the variable selection and the rule development. The error reduction of almost the 50% leads to a great improvement of the system performance in view of its implementation for real time control. It is to be underlined that the proposed approach is the first attempt to design an automatic identifier for the regime classification and the L-H transition problem at JET, starting only from the data available: it will be further tested on a wider database to fully assess its performance and minimize human contribution.

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