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Comparison Between Cart and Fuzzy Logic for Confinement Regime Classification at JET

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** See annex of M.L. Watkins et al, "Overview of JET Results",*
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ABSTRACT
Thermonuclear fusion devices of the Tokamak type can operate in distinct confinement regimes, which present different properties in terms of performance and plasma parameters. Discriminating among them in real time would represent a useful advantage for an efficient control of the experiments. A comparison between two automatic identifiers, one based on fuzzy logic and another based on classification and regression trees, is presented. A robustness assessment, adding Gaussian white noise to the input signals, was performed to determine the properties of the two approaches in realistic experimental conditions.

1. INTRODUCTION
Nowadays the most promising strategy to achieve nuclear fusion consists of heating a plasma of hydrogen isotopes 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, great efforts have been exerted to improve the power balance of thermonuclear fusion plasmas. Although the obtained performance is not sufficient for economic exploitation yet, significant improvements in plasma control and confinement have been obtained together with a relevant increase in the knowledge of the physics underlying magnetic confinement.

Among the various achievements, 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, the plasma underwent an abrupt transition to an improved confinement mode, called H-mode for High confinement. The H-mode 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. Carefully controlling this regime during the experiments is then desirable in order to maximize the performance. To achieve that, an adequate real time control strategy should be implemented, contrary to what happens in today experiments where the confinement regime is assumed a priori to evolve according to a redefined sequence defined before the beginning of the discharge. As already reported in ASDEX Upgrade [1], with this feedforward strategy, unexpected variations in the plasma confinement state can induce the real time controller to 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 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.

The first attempt were made by Franzen *et al*. [2], Martin and Bühlmann [3] and Giannone *et al*. [4].

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 Dα signal since this is one of the main quantities 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 three different techniques: Fuzzy Logic (FL), Support Vector Machine (SVM) and Discriminant Analysis. In [5], the choice of the variables to be provided to the FL and SVM identifiers was driven by the need to include the Dα in the set of parameters describing the plasma and to minimize the dependence on engineering parameters using derivatives or normalized signals. In a subsequent work [6], the authors proposed 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) [7] method was undertaken to assess the relative importance of the various signals. The output of CART was then used to devise a FL classifier. In this work the authors propose a robustness analysis of the relative importance assessment produced by CART, evaluating the relative importance of the same variables when a white Gaussian noise is superimposed to the diagnostic signals. Moreover, a comparison of the classification results produced by CART and the FL based identifiers is reported.

2. RELATIVE IMPORTANCE EVALUATION ROBUSTNESS

In order to investigate the relative importance of the signals given as input to the classifier, a feature selection analysis based on the Classification and Regression Trees has been performed. It is a non-parametric statistical method, which uses a decision tree to solve classification and regression problems using both categorical and continuous variables.

This approach was introduced by Breiman *et al*. [7] to build a decision tree, which describes one output variable as a function of different explanatory variables. When the output is categorical, CART produces a classification tree, whereas if the output is continuous the result is a regression tree. CART evaluates the importance of the different variables, to describe the output in the selected dataset, trough the so-called "variable ranking method". Variable importance is the sum across all nodes in the tree of the improvement scores that the variable induces when it acts as a splitter in a node. The importance values so obtained allow ranking the different input signals from high to low explanatory power. In this way, CART can be used for feature selection, being able to identify the most important variables to describe the output.

Table 1, for instance, reports the variable ranking when all the variables in the database are used as input to the classification tree. It is possible to observe that only the first six quantities appear to contribute significantly to the classification process.

In order to assess the robustness of this relative importance evaluation, a classification tree was built with the same input variables but with a white Gaussian noise added to the signals. The variable ranking for different Signal to Noise Ratios (SNR) is reported in Table 2. Also in this case the number of variables which contribute significantly to the classification process is six. However, when the SNR decreases the *Ptot* signal seems to become more relevant and to substitute Dα inner spectrum integral. This is not to be considered a real effect, since the value of the input power is known very well with a S/N ratio of the order of the one assumed in the two first columns of table II.

3. COMPARISON BETWEEN CART AND FUZZY LOGIC

Apart from providing information on the variable ranking, CART can also be used to classify the inputs directly. Part of the database can be used to train the tree while the remainder part of the database can be used for testing the produced tree. Compared to other classification techniques, classification trees have several advantages among which the most important are: intuitive interpretation, little data preparation requirements, use of a white box model and the capability to process easily large amount of data.

CART has been, then, tested as classifier using 75% of the database as training set and the remainder as testing set. Its performance was compared with the Fuzzy Logic approach already devised by the authors in [6]. Figure 1 and Figure 2 report this comparison. Figure 1 shows the different percentage of correct classifications for both FL and CART using the same testing set. The performance evaluation was carried out using the database with superimposed white Gaussian noise to obtain different SNR values.

Figure 2 reports the same comparison but using as inputs only the sample in proximity to (0.5 s before and after) the L to H and H to L transitions.

In the first case, even if the FL is always outperforming CART, the two results are comparable for high SNR ratios. The CART performance, however, degrade faster than FL when the SNR decreases. Closer to the L-H transition, the trend is similar but FL presents a rate of success more than 10% higher than CART even at the best SNR values.

CONCLUSIONS

A classification tree method was employed to determine the relative importance of different diagnostic signals in the discrimination of the confinement regime at JET. Its output was then used to select among the diagnostic signals the most suitable for devising a fuzzy logic classifier. The variable ranking robustness was evaluated building a classification tree with noisy inputs. The results demonstrated that the chosen variables remain the most important for all realistic levels of signal to noise ratio.

The classification tree was also exploited to classify the database. To this end, part of the database was used as training set while the remainder as testing set. In all cases, utilizing the whole dataset or just the samples near the transitions, with or without noise, the FL devised starting from the output of the classification tree as described in [6] is always outperforming the classification tree itself. On the other hand, the CART approach is simple, intuitive and with low computational burden. These results demonstrate that the proposed approach, i.e. use the CART to select the most relevant inputs and to provide starting information in order to devise a fuzzy network, is promising.

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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}	1,08
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,	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.

	SNR50		SNR40		SNR 30		SNR 20
β_N	100,00	β_N	100,00	β_N	100,00	β_N	100,00
W_{mhd}	87,14	W_{mhd}	86,65	W_{mhd}	87,81	W_{mhd}	89,42
Dens	82,64	Dens	82,52	Dens	80,34	Dens	78,20
$D\alpha_{outer}$-SI	75,41	P_{tot}	73,91	P_{tot}	75,87	P_{tot}	77,68
$D\alpha_{inner}$-SI	73,16	$D\alpha_{outer}$-SI	70,88	$D\alpha_{vertical}$-SI	65,41	$D\alpha_{vertical}$-SI	61,33
$D_{vertical}$-SI	70,06	$D\alpha_{vertical}$-SI	69,17	$D\alpha_{outer}$-SI	65,39	$D\alpha_{outer}$-SI	53,92
FDWDT	3,69	FDWDT	2,92	FDWDT	2,49	FDWDT	3,04
$D\alpha_{inner}$-CC	2,04	$D\alpha_{outer}$-CC	2,39	Ipab	2,02	$d\beta_N/dt$	1,37
Ipab	1,96	$D\alpha_{inner}$-CC	2,29	K	1,89	Ipab	1,35
K	1,95	$D\alpha_{inner}$	2,20	$D\alpha_{outer}$-CC	1,61	$D\alpha_{inner}$-SI	0,79
$D\alpha_{inner}$	1,80	$D\alpha_{outer}$	2,14	$D\alpha_{outer}$	1,49	K	0,75
$D\alpha_{outer}$	1,78	K	1,57	$D\alpha_{inner}$-CC	0,79	$D\alpha_{outer}$	0,67
Q_{95}	1,36	$D\alpha_{vertical}$	0,94	$D\alpha_{vertical}$-CC	0,73	$D\alpha_{outer}$-CC	0,64
$D\alpha_{vertical}$-CC	1,01	Q_{95}	0,85	Q_{95}	0,70	B_T	0,55
$D\alpha_{outer}$-CC	0,93	Ipab	0,77	$D\alpha_{inner}$	0,63	$D\alpha_{vertical}$	0,51
P_{tot}	0,90	$D_{vertical}$-CC	0,76	$d\beta_N/dt$	0,41	$D\alpha_{inner}$-CC	0,49
LI	0,82	$d\beta_N/dt$	0,75	$dD\alpha_{inner}$-CC/dt	0,40	$dD\alpha_{outer}$-CC/dt	0,47
$D\alpha_{vertical}$	0,72	$D\alpha_{inner}$-SI	0,64	$D\alpha_{vertical}$	0,35	$D\alpha_{inner}$	0,45

Table 2: Relative importance of the various signals used as classifiers in CART when a white Gaussian noise with different SNR is superimposed to the signal. The least important signals have been removed for space reasons.

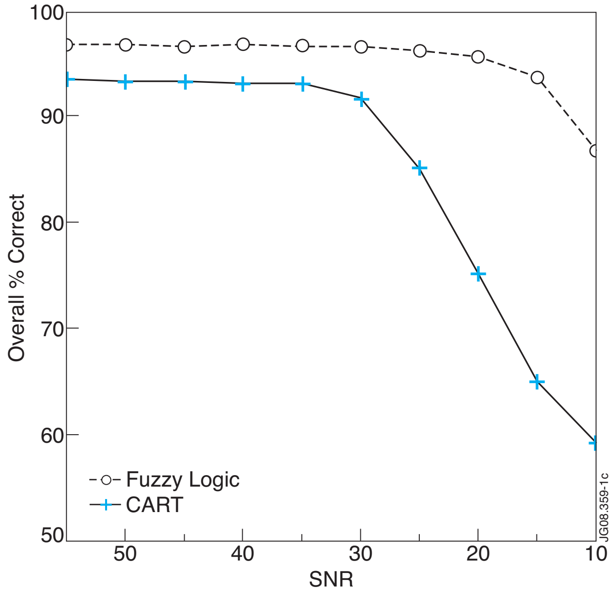

Figure 1: Comparison between the fuzzy logic and CART classifier when evaluating the full length data with superimposed Gaussian white noise with different Signal to Noise Ratios (SNR).

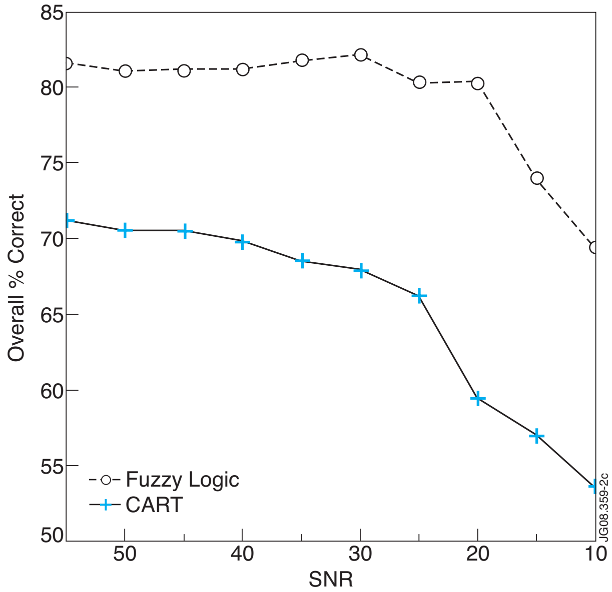

Figure 2: Comparison between the fuzzy logic and CART classifier when evaluating the data 0.5s before and after the L to H and H to L transitions, with superimposed Gaussian white noise with different Signal to Noise Ratios (SNR).