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ABSTRACT.
Disruptions are mayor instabilities and remain one of the main problems in Tokamaks' operation. Using JET (Joint European Torus) database, a disruption predictor is developed using exploratory data analysis methods and supervised learning techniques. The main objective of the work consists of determining how much in advance of the disruption a classifier can operate with acceptable success rate.

1. INTRODUCTION

One of the most dangerous events in Tokamak operation are disruptions, uncontrolled losses of plasma current and consequently of confinement. It is generally accepted that they evolve in 4 phases [1]: initiating event, precursor phase, thermal quench and current quench. Disruptions are preceded by a series of abnormalities in the plasma behavior that can in principle be detected in order to undertake corrective action. The high non linearities in the phenomena leading to a disruption have prevented up to now the identification of models to forecast disruptions with sufficient reliability. To deal with this problem, a classification procedure, based on exploratory data analysis and supervised machine learning methods, has been developed. The determination of the maximum time in advance in which disruptive behaviors could be recognized and the classification results with a detailed rate of success at different times are reported.

2. MACHINE LEARNING CONCEPTS

This work is focused on the recognition of disruptions. A wide set of methods, classified as "Machine Learning" techniques, is appropriated for that purpose. They have been developed to allow computers to "learn" and distinguish different classes of objects. Specifically, the "supervised learning methods" assign, during the training process, to each input object (in this case discharges) previously known target outputs (disruptive or non-disruptive), building a general model. Therefore, the training consists in supplying the system with a set of known inputs and specifying their condition (disruptive or not). Once the system has been trained, the next step is testing its performance. It is done by inputting to the trained system a new test set of discharges to be classified. Accordingly, the dataset of discharges has to be split in two groups: the first one for training and the other one for testing. The training and testing data sets have been chosen randomly. Therefore, to avoid the presence of bias in the haphazard selection, the n-fold cross validation method [2] has been applied. Typically, it is used in small data sets and it is characterized by low bias. It consists of splitting randomly the available database in n groups (each one with the same amount of haphazardly selected disruptive and non disruptive pulses), keeping one of the groups for testing and the other n-1 for training. This procedure is repeated n times, leaving in each occasion a different group for test. Finally, n rates are computed separately and the final percentages are the average of the n values.

Lastly, it is significant to highlight a main point, which is crucial to obtain reliable outcomes in any classification system: each input must represent the principal characteristics of the discharges in an adequate format. Generally, the available data must be processed and its principal characteristics are represented in “feature vectors”.

3. DATABASE

The dataset utilized for this research contains 220 disruptive and 220 non-disruptive discharges taken from the JET database. Taking into account previous research [3, 4], each shot is represented by the temporal evolution of 13 signals: the plasma current, the poloidal beta and its derivative, the mode lock amplitude, the safety factor at 95% of minor radius and its derivative, the total input power, the plasma internal inductance and its derivative, the plasma vertical position, the plasma density, the stored diamagnetic energy derivative and the net power (total input power minus total radiated power).

To standardize the available database some preprocessing has been necessary. The sampling rate is unequal in the available signals, so an interpolation algorithm has been applied to each one (giving a sample every millisecond). A “disruptive-equivalent” time has to be assigned to the non-disruptive shots. This instant has been calculated following the criterion adopted in a previous work [5] i.e. seven seconds after the plasma reaches the X-point configuration.

4. FEATURE VECTORS

To represent the characteristics of the 13 signals in a single vector, several perspectives were considered. A scheme of the feature extraction procedure is depicted in Figure 1. It consists of splitting each signal in temporal segments of 30 ms (TS), a time interval that proved to be long enough to show plasma tendencies. These 13 TS are concatenated in a single “feature vector” per pulse. However, the consequence of the wide variety of signals is the high differences in amplitude between them. To ensure that all TS contribute with equal weights to the classification process, normalizations have to be applied according to the formula:

$$Normalizated\_signal = \frac{Raw\_signal - Min}{Max - Min}$$

where Min and Max, respectively, represent the minimum and maximum values of each signal in the dataset. Applying the procedure to the whole database, a first dataset of “normalized feature vectors” (FV1) is developed. It contains 13 “normalized” TS per shot, with a considerable dimensionality (390 values from 13 signals, each one with 30 samples).

Since no general method exists for the extraction of the features more relevant for a given classification problem, an heuristic analysis has to be performed. In the present case, a visual inspection evidences high frequency components in the signals of disruptive discharges. This suggests a frequency analysis for the feature extraction process. Consequently, the DFT (Discrete Fourier Transform) has been applied to each TS stored in the FV1. Looking for a high dimensionality reduction, only the standard deviation of the positive frequency spectrum was retained. Hence, a new set of feature vectors (FV2) containing one value per signal and consequently 13 per discharge has been created.

Finally, an even greater dimensionality lessening is achieved by applying the Principal Component Analysis (PCA) [6] to the FV2. PCA tackles the feature extraction and dimensionality reduction accounting for how much the original data, in the reduced feature space, varies. The number of components that should be kept has been determined by a scree plot [7]. Following this exploratory activity, 3 components have been chosen for the alternative feature vector (FV3).

5. EXPLORATORY DATA ANALYSIS

One of the aims of this article is to provide an estimation of how long in advance the disruptive phenomenon can be detected. To this end, the three feature vector collections (FV1, FV2 and FV3) have been used. They were inputs to graphical methods of exploratory data analysis (EDA). Due to the fact that there are two different sets of discharges (disruptive and non-disruptive), it would be expected to visualise two different groupings (clusters) in the data. As feature vectors are closer to the disruption, a more clear distinction between clusters would have to be shown. On the contrary much in advance of the disruption, the distinction is expected to completely disappear. The loss of predictive power is not abrupt and one of the intermediate segments can be used as an estimation of the precursor time. Of course, this value is dependent on the attributes represented by the feature vectors and, therefore, it must not be taken in absolute terms. In other words, there is no guarantee that other attributes, different from the ones selected in this work, could find earlier precursors of the disruptive instability. Generative Topographic Maps (GTM) [10] has been used as EDA method. GTM defines a non-linear parametric mapping of the available data in a reduced dimensional space (2D), maintaining the relative distances of the data of the original input space. This technique allows observing the clustering in the data at different times before the disruption (figure 2). The grey points represent the low dimensional mapping of the non disruptive discharges and the black ones symbolize the disruptive ones. The transition between clear separation and overlap of the points in the selected feature space corresponds to the interval [-210, -180].

6. SUPERVISED IDENTIFICATION

Three supervised learning systems for discharge identification have been developed. They were based on Support Vector Machines (SVM) [8], because its simplicity (i.e. it is not necessary to predefine number of hidden neurons as in Neural Networks) and good performances. SVM exploits transforming functions called kernels to solve non-linear separation problems. The SVM software called “spider” [9] (included in the public licensed environment for MATLAB®) has been used.

In the test stage, the rates of success are measured as follows: if the system correctly determines the class of the new shot, it will be counted as a correct classification. The misclassifications are divided in two groups: when a non disruptive pulse is misclassified, it is counted as a False Alarm, and if a disruptive discharge is not correctly recognized the error counts as Missed Alarm. The comparison of the results for the 3 classification systems with the 3 feature vector collections is depicted in figure 3. As it can be seen, classification rates above 90% are achieved about 200ms before the disruption, with a maximum of 99% 30ms before it occurs. The missed and false alarms are represented just for the best performance case: data whose feature vectors were FV2. The tested kernels in the SVM system are polynomials, radial basis functions and linear, the last one giving the high performances represented in Figure 3.

DISCUSSION

The results prove that the signals show disruptive behaviors about 200 ms before a disruption. Although GTM maps begin to mix disruptive and non-disruptive discharges in the segment [-210, -180], SVM helps in distinguishing both behaviors through the use of Kernel functions. To conclude, different classification systems have been developed and high recognition rates have been achieved. The next step should be centered on adapting the system with the goal of developing realtime applications.

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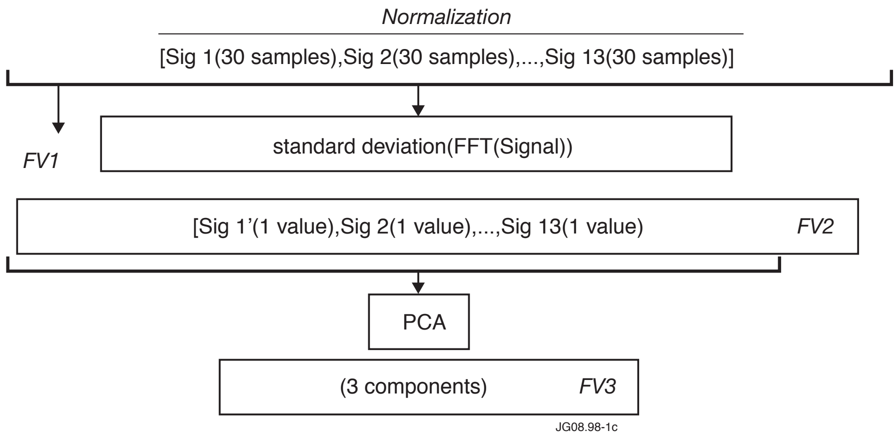

Figure 1. Feature Extraction Procedure

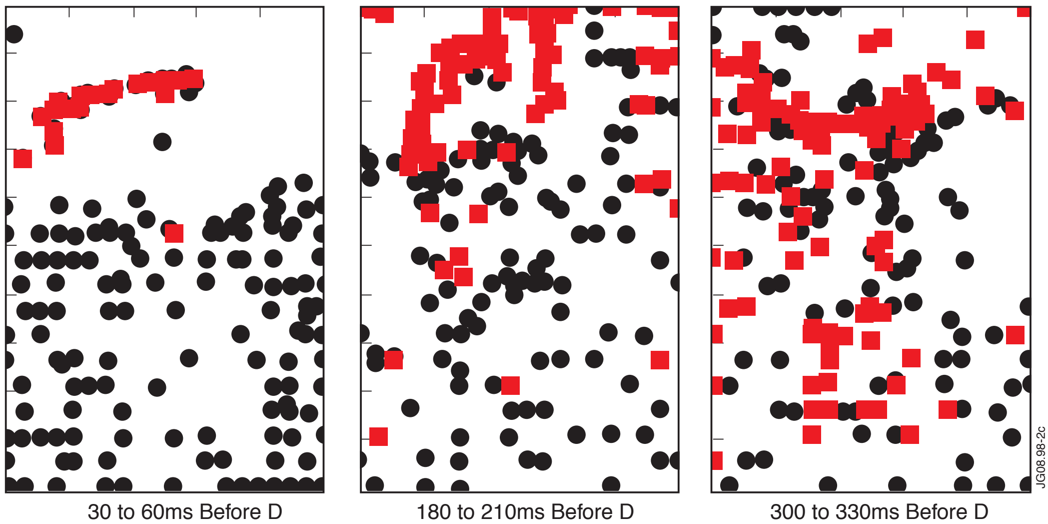

Figure 2. GTM 2D mapping.

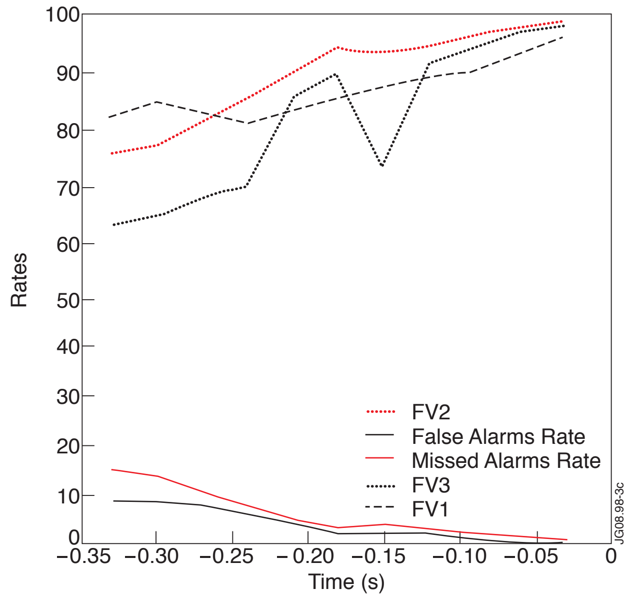

Figure 3: Overall Classification Rates.