Feature extraction for improved disruption prediction analysis at JET

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Feature extraction for improved disruption prediction analysis at JET[a)]

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Disruptions are major instabilities and remain one of the main problems in tokomaks. Using Joint European Torus database, a disruption predictor is developed by computational methods including supervised learning techniques. The main objectives of the work are to develop accurate automatic classifiers, to test their performances, and to determine how much in advance of the disruption they can operate with acceptable reliability.
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INTRODUCTION

Several papers about disruption predictions at JET have been published in the past years applying learning methods.[1,2] However, the achieved percentages of correct classifications were not completely satisfactory, reaching maximum performance of about 91% success rate.[3] The aim of the present work is to obtain higher recognition rates, maintaining a low rate of missed and false alarms. To improve the previous results, it has been necessary to exhaustively preprocess the selected signals, extracting their more disruptive-relevant characteristics in a so called feature extraction procedure. In this framework, it is also relevant to identify how much in advance the incoming disruption begins to become evident in the signals. This last issue was only studied before by means of a heuristic procedure at ASDEX Upgrade.[4] To identify this time at JET, a specific effort has been devoted to perform a deeper study using machine learning techniques with high time resolution by the exhaustive analysis of the discharge evolution every 30 ms.

MACHINE LEARNING CONCEPTS

Machine learning is the name given to a set of techniques aimed at allowing computers to "learn." By detecting significant patterns in the available data, a system based on these techniques can make predictions about new data coming from the same physical object or source. In this sense, the system has acquired generalization power by "learning" something about the source generating the data.

Supervised methods are a category of machine learning techniques for automatic classification. The learning is based on a set of input objects together with the information about which class they belong to. In the present case, the input objects are signals of JET discharges and the possible classes are two: disruptive and nondisruptive. This learning stage is called training, and through it, a general model is built. Once the system has been trained, the next step consists of testing its performance. It is done by inputting to the system a test set of discharges to be classified and counting the rate of successful classifications in terms of percentages.

One of the advantages of this method is that it makes no necessary a tedious and probably inaccurate tabulation of parameters. Tabulating parameters can be useful for simple classifications with a reduced dimensionality. In the present study, the dimensionality is high. Therefore, taking care of the big variety of all possible situations (variation ranges depending on parameter combination) would result in a tedious and probably imprecise code development. Learning systems perform this in the most optimal way.

TRACKING PROCEDURE AND DATABASE

To track the evolution of the discharges, time windows are analyzed to create a classification system every 30 ms. Each time window (or temporal segment of signal) is linked to the time when the disruption occurs. So, for nondisruptive shots a "disruptive-equivalent" time had to be assigned to match times in disruptive discharges. This instant has been calculated following the criterion adopted in a previous work,[2] i.e., 7 s after the plasma *X*-point creation.

The dataset utilized in this study contains 220 disruptive and 220 nondisruptive discharges from the JET database. Considering previous research,[2,3] each shot is represented by the temporal evolution of 13 signals: the plasma current, the poloidal beta and its time derivative, the mode lock amplitude, the safety factor at 95% of minor radius and its time derivative, the total input power, the plasma internal inductance and its time derivative, the plasma vertical position, the plasma density, the stored diamagnetic energy time deriva-

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[b)]For a full listing of names and affiliations of the JET-EFDA Contributors, see A. T. Macrander, Rev. Sci. Instrum. **79**, 10F701 (2008).
[c)]See the Appendix of M.L.Watkins *et al.*, Fusion Energy 2006 (Proceedings of the 21st International Conference, Chengdu, 2006) IAEA, (2006).

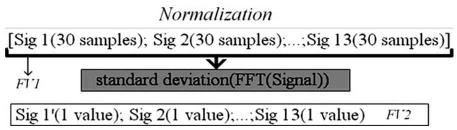

FIG. 1. Scheme of the feature extraction procedure performed to each temporal window.

tive, and the net power (total input power *minus* total radiated power).

The sampling rate is unequal in the available signals, so an interpolation algorithm has been applied to each one (resampling the signals to achieve a resolution of 1 ms) to standardize the available database. The 13 signals used present amplitudes which differ by several orders of magnitude. That matter is counterproductive for a classification system. The system could give too high weights to certain signals because of their absolute values and not because of their relevance for the prediction. Therefore the signals have been normalized according to the formula

$$\text{normalized signal} = (\text{signal} - \text{min})/(\text{max} - \text{min}),$$

where min and max, respectively, represent the minimum and maximum values of each signal in the dataset.

FEATURE EXTRACTION

Feature extraction is the process leading to the identification of the most suited feature vectors to be used as inputs in the classification systems. The general procedure adopted for the classifiers is summarized in Fig. 1. It begins by splitting each signal of a pulse in temporal segments of 30 ms. This time window was chosen as a compromise between time resolution and capability to show plasma tendencies. Equivalent temporal segments of each one of the 13 signals are concatenated, generating a basic "feature vector" every 30 ms. This procedure is extended to all the time periods, providing a complete collection of feature vectors per shot.

Applying the previously explained procedure to the whole database, a first dataset of feature vectors (FV1) is obtained. For each 30 ms time window, each feature vector of the FV1 collection contains 390 attributes. Those attributes are the result of the concatenation of the 30 samples (1 sample per millisecond) of the 13 signals.

Besides, a simple visual inspection of the signals reveals very clearly the presence of higher frequency component behavior as the discharge approaches a disruption. Consequently, frequency analysis should be included in the feature vectors. Therefore, the fast Fourier transform has been applied to each temporal segment stored in the set of FV1. Only the standard deviation of the positive frequency spectrum has been retained. Hence, an alternative set of feature vectors (FV2), containing 13 attributes (one value per signal in the temporal segment), has been derived.

CLASSIFICATION SYSTEMS

In the present work, to build the classifiers, a software based on support vector machines[5] (SVMs) has been implemented for two reasons: its simplicity (i.e., it is not necessary to predefine number of hidden neurons as in neural networks) and its good performances. SVM exploits transforming functions called *kernels* to solve nonlinear separation problems. The SVM software called spider[6] (included in the public licensed environment for MATLAB® has been used.

The training of each system is performed inputting the 70% (randomly selected) of the whole set of feature vectors corresponding to a time interval to the SVM system. The remaining 30% is used for testing. The misclassifications are divided in two groups: when a nondisruptive 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.

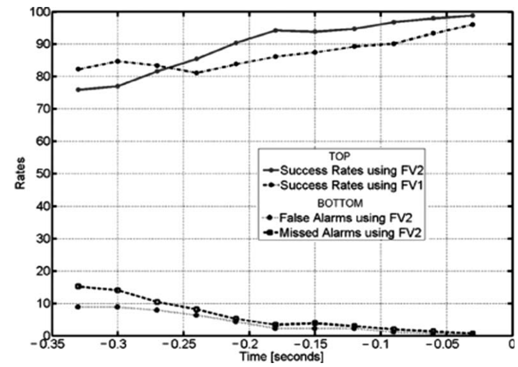

FIG. 2. Overall classification rates.

RESULTS AND DISCUSSION

The comparison of the results with two different collections of characteristics is depicted in Fig. 2. Each point corresponds to a classification system for a 30 ms time interval. The 0 in the abscise axis identifies the disruption time. The time window $[-30, 0]$ ms before the disruption has not been included for being too close to the disruption time and therefore not giving enough margins to take any possible remedial action. The best classification rates are achieved with the FV2 collection, proving to be a better input than FV1. The success rates are above 98.5% 30 ms before the disruption and remain high (above 93%) 180 ms before it occurs. The missed and false alarms are represented just for the data corresponding to the FV2. The tested kernels in the SVM system are polynomials, radial basis functions, and linear, the last one giving the high performances shown in Fig. 2.

The results prove that the closer the shots are to the disruption, the higher classification rates can be achieved. A relevant fact can be noticed: earlier than 180 ms before the disruption, the obtained classification rates decay considerably. That time can be considered the maximum in advance able to predict reliably an incoming disruption.

For the collection of characteristics labeled FV2, the classification rates are globally the highest achieved at JET. However, this classifier has not been tested in real time yet. A possible strategy to predict an incoming disruption could consist of undertaking remedial action after the classifiers provide an alarm for two successive time intervals. The next step of the research should be focused on devising the best methods for a real-time application of these classifiers.

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