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Latest Developments in Data Analysis Tools for Disruption Prediction and for the Exploration of Multimachine Operational Spaces

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ABSTRACT.
In the last years significant efforts have been devoted to the development of advanced data analysis tools to both predict the occurrence of disruptions and to investigate the operational spaces of devices, with the long term goal of advancing the understanding of the physics of these events and to prepare for ITER. On JET the latest generation of the disruption predictor called APODIS has been deployed in the real time network during the last campaigns with the new metallic wall. Even if it was trained only with discharges with the carbon wall, it has reached very good performance, with both missed alarms and false alarms in the order of a few percent (and strategies to improve the performance have already been identified). Since for the optimisation of the mitigation measures, predicting also the type of disruption is considered to be also very important, a new clustering method, based on the geodesic distance on a probabilistic manifold, has been developed. This technique allows automatic classification of an incoming disruption with a success rate of better than 85%. Various other manifold learning tools, particularly Principal Component Analysis and Self Organised Maps, are also producing very interesting results in the comparative analysis of JET and ASDEX Upgrade (AUG) operational spaces, on the route to developing predictors capable of extrapolating from one device to another.

1. INTRODUCTION

Predicting the future is a fundamental task because it allows better decision making and more conscious planning. Forecasting has therefore become the core business of many human activities, ranging from insurance and financial companies to logistics and prospecting. Even in science two of the most outstanding problems, with a great potential to influence our civilization, involve forecasting: the prediction of earthquakes and of long term climate changes [1].

In nuclear fusion one of the critical unsolved problems concerns disruptions prediction, since in the next generation of devices they can have disastrous consequences for the integrity of the machines. Disruptions are unavoidable in current tokamaks and accurate and reliable predictions are a prerequisite to any mitigation strategy [2]. In ITER, the success rate of disruption predictors should be very high to prevent a too fast erosion of the divertor. In the last years, particularly on JET with the new wall, it has become evident that to optimise the mitigation strategy it would be important also to predict the type and not only the imminence of a disruption. On the other hand, disruptions have proven to be quite difficult to model theoretically. This is due to the fact that they are very complex, nonlinear events, which can be triggered by a variety of instabilities. Therefore the most recent efforts in data analysis have concentrated on predictors based on machine learning tools (see Section 2). In this perspective, two main aspects have been pursued recently: the improvement of the success rate of the predictors and the automatic classification of disruptions (see Section 2). Various alternatives solutions can be conceived to improve the success rate of the predictors but all the solutions of practical interest have been trained with a large number of examples and require exploring a very high dimensional space (the majority of most successful predictors reported in the literature typically use about ten different features of the plasma, an exception is reported in [3]). In the next generation of devices (namely ITER), it is not considered feasible to wait for a large number of disruptions in order to train complex predictors. On the other hand, the huge quantity and high-dimensionality of diagnostic signals, which can be considered useful disruption precursors, pose significant challenges to the comprehension of the information contained in the data. Developing tools which can help in exploring the operational space, would therefore be beneficial for both assessing whether predictors can be extrapolated from one device to another and for the understanding of the disruption causes. A possible approach consists of trying to determine whether the relevant information lies on an embedded, possibly non-linear, manifold within the higher-dimensional space of the selected features. If this proved feasible, the data could be represented well in a low-dimensional subspace and more effectively analysed to extract information about the physics of the disruptions and their precursors. From a practical point of view, this approach can also be used to assess whether the operational spaces of different devices are similar and therefore to what extent predictors trained with the examples of one device can be extrapolated to a different, typically larger device (see Section 3). This aspect has of course strong implications for the strategy to prepare predictors for ITER.

2. DISRUPTION PREDICTION AND DISRUPTION CLASSIFICATION

In the perspective of pushing the boundaries of predictor performance, the Advanced Predictor Of DISruptions (APODIS) has been refined and in its most recent configuration it presents the architecture shown in figure 1 [4,5]. It consists of a combination of supervised classification systems, based on SVM (Support Vector Machines) organised in two layers. The first layer contains a series of three different SVM predictors, analysing three consecutive time windows (each 32 ms long) of data to take into account the history of the discharge. The outputs of these three evaluations are used as inputs to the second layer classifier, which takes the final decision whether or not to launch an alarm. APODIS has been conceived to run in real time, employing typical signals used for prediction. It has been applied to a large database of JET discharges, covering all the shots in campaigns from C15 to C27b, in which the required measurements are available. The training and testing of the predictor has therefore been performed using various features (all derived from signals available in real time), for hundred of shots selected among more than 8400 discharges analysed using high performance computation tools. The performance is reported in Figure 2 for the most recent campaigns with the carbon wall and using the real time version of the following signals: plasma current (in Ampere), plasma density (in m^{-3}), derivative of the stored diamagnetic energy (in Joule), mode locked amplitude (in Tesla), radiated power (in Watt), total input power (in Watt). It is worth noticing that in the campaigns (C24, C25, C27a) with good quality signals and without the use of magnetic perturbation for ELM mitigation, not included in the training set, the success rate of the predictor is typically of the order of 90% at least 32 ms before the disruption (for a rate of false alarms of a few percent). Starting in campaign C30 with the ITER-like wall APODIS has been run in JET real time network from shot 82429 to shot 83716. In this interval, 305 discharges were affected by non intentional disruptions. Such a number of disruptive shots constitute a quite good statistical basis, since this is almost the same number of disruptions which occurred in the period covering campaigns C20-C27b (amounting to various years of JET operation). The results of APODIS are very positive as shown in Table I. The number of false alarms is very limited. The success rate is very high and the mean value of the APODIS prediction time is 426ms in advance to the disruption (between 1 ms and 10.323 s). It should be mentioned that the minimum estimated time to carry out mitigation actions in JET is 30 ms. At this time, APODIS has recognized 90% of all unintentional disruptions. The only few missed disruptions are due to the poor resolution of the used implementation of the predictor, which waits for the data of the subsequent 32 ms before making a new prediction. A new version of the code, based on sliding windows, has been developed [5]. This new version can perform a new prediction in 300 ms, well within the cycle time of JET ATM network (2ms). It has been checked that with this increased time resolution APODIS manages to predict also the few missed alarms; it is therefore planned to deploy this new implementation of APODIS in real time in the next set of JET campaigns.

A very accurate and timely prediction of disruptions can now be achieved with APODIS but this is no always sufficient to decide the most appropriate mitigation technique. A significant improvement in the strategy to react and to land the plasma could be achieved if it were possible to know in advance the type of disruption about to occur. In JET a database is available with the classification of the disruptions performed manually by the experts [6]. The main classes of disruptions are reported in Table II. In this perspective, a new approach is proposed, based on the geodesic distance on a probabilistic manifold and on clustering. The main idea behind the approach consists of building clusters of disruptions belonging to the same class. Once a new disruption is detected, an appropriate technique must determine which is the most probable cluster the new discharge belongs to. In practically all the applications in fusion, the clustering technique is based on the Euclidean distance. This is unsatisfactory in our application since the measurements provided by the diagnostics are affected by non negligible error bars. Assuming, as it is typically done, that these uncertainties can be represented mathematically by Gaussian distributions, the various examples can be considered lying on a probabilistic manifold. The distance between two Gaussians on this probabilistic manifold can be expressed in closed form by relation (1).

$$GD(p_1 \| p_2) = \sqrt{2}\ln\frac{1+\delta}{1-\delta} = 2\sqrt{2}\tanh^{-1}\delta,\ \ where\, \delta = {\frac{(\mu_1-\mu_2)^2+2(\sigma_1-\sigma_2)^2}{(\mu_1-\mu_2)^2+2(\sigma_1+\sigma_2)^2}}^{1/2} \tag{1}$$

where μ_i are the means and μ_i are the standard deviations of the two Guassians. Expressing the distance between discharges with relation (1) allows taking into account the error bars of the measurements in the clustering process to identify the type of disruption more likely to occur [7]. To apply the approach to JET, the same signals used by APODIS and available in real time have been analysed. To test the performance of the clustering approach, a database of 728 disruptions between number 49948 and number 79831 has been analysed and clustered in the classes of Table II. In this first analysis, the main objective has been simply to test the potential success rate of the proposed clustering. Therefore each disruptive shot has been treated as a new case to classify, while it has been assumed that all the other examples had already been classified by the experts in their correct clusters. The distance between each disruptive shot and all the other discharges, present in the data base and already classified, has been calculated. The new example has then been included in a certain cluster according to the criterion of the nearest neighbour. The success rate of the method, defined as the agreement between the expert and the automated classification, is reported in Figure 3 for the last 300 ms before the occurrence of the disruptions. The evaluation of the success rate has been performed every 10 ms in this interval. As can be seen, the classification based in the geodesic distance on the probabilistic manifold outperforms clearly the Euclidean distance at all times. The improvements of about 5 % is also statistically significant since it brings the overall success rate to about 85%, which starts being a quite interesting success rate. This is more so since the classification of the experts, considered here the reference, is also not to be considered 100 % accurate. The score for every single type of disruption is shown in Figure 4; it is worth mentioning that the geodesic distance improves the success rate for the classification of each single type of disruption compared to the Euclidean distance.

3. MANIFOLD LEARNING FOR PHYSICAL STUDIES AND EXTRAPOLATION

The predictors of the complexity of APODIS can reach very good performance but they have been trained with a very high number of examples, which are not expected to be available in the next generation of devices. Moreover the results of predictors of the complexity of APODIS are quite difficult to relate to physical theories of disruptions. Tools of higher interpretability are required to investigate the physics of disruptions (even at the price of reduced performance in terms of prediction accuracy) and to determine to what extent tools trained on one device can be extrapolated to another. A recent data driven approach, with great potential to contribute to the understanding of disruption mechanisms, consists of trying to determine whether the relevant information lies on an embedded, possibly non-linear, manifold within the higher-dimensional space. If this proved feasible, the data could be represented well in a low-dimensional subspace and more effectively analysed to extract information about the physics of the disruptions, their precursors and the chances of extrapolating from one device to another. To this end, recently, dimensionality reduction and manifold learning methods have been actively investigated, using various tools ranging from Data Tours to Principal Component Analysis and Self Organising Maps (SOM) [8,9,10].

As a first step, it has been decided to investigate whether the operational spaces of JET and AUG (as limited by the occurrence of disruptions) present the same dimensionality. If this were not the case, the chances of being able to extrapolate from one device to another would be extremely small. In order to investigate this point, Principal Component Analysis has been applied to two large databases of disruptions, one for each device. JET database is composed of the last 210 ms of

82 disruptive discharges and 500 safe ones, selected from campaigns from C15 (year 2005) up to C27b (year2009). Therefore this data set covers the last campaigns of JET with a carbon wall. AUG database is composed of the last 45 ms of 348 disruptive discharges and 1150 safe ones, selected from the AUG experimental campaigns carried out between 2002 and 2009. The choice of the shots has been driven mainly by the availability of the required signals.

The plasma parameters considered in the analysis for both machines are listed in Table III. The chosen quantities are mainly non dimensional parameters and therefore are particularly suited to multimachine investigations. Moreover, they are quantities which are either already available in real time in both devices or which could be provided in real time without major difficulties, since they are based on quantities routinely measured.

Both datasets have been analysed using the PCA method to determine whether the two operational spaces present the same dimensionality at least in terms of principal components. The variance retained by each principal component and the cumulative variance retained for a progressive number of components have been calculated and the results are reported in Table IV. What is remarkable in this table is the fact that the various principal components account for more or less the same amount of the variance in the data for both machines. Moreover, for both data sets, the first five principal components explain about 90% of the variance. These results are encouraging since they could indicate that the operational spaces of the two devices are relatively similar. Therefore predictors trained on one of the devices could be quite effective when deployed on the other. On the other hand, the tool (PCA) used to perform the analysis just presented is a linear technique. The most relevant information for disruption prediction could be located on a nonlinear manifold of lower dimensionality. To start investigating this point, the operational spaces for JET and AUG are projected in two dimensions using SOM to determine whether clear indications about the boundary between safe and disruptive regions can be identified. The same plasma parameters have been mapped for both devices (see Table III). In both cases, the maps, shown in figure 5, clearly highlight the presence of a large safe region (green clusters) with an associated low risk of disruption, some disruptive regions (red clusters), with a high risk of disruption, well separated from the safe region by transition (gray clusters) and empty regions (white clusters). JET operational space seems to be more complex to map and would possibly require the use of other precursor signals. The future directions of this line of research include the ambitious task of training a predictor with one machine and extrapolating it to the other experiment.

CONCLUSIONS

In the last years the predictor APODIS has been developed. On the basis of a training based on thousands of discharges (with the carbon wall), it has been possible to obtain very high success rates in the real time implementation during the campaigns with the ILW. Practically all the 305 disruptions have been detected: the five missed were due to the limited time resolution of the implemented version of APODIS (32ms). With the sliding version of the predictor also these 5 disruptions are properly detected. The number of false alarms is also very low and typically due to problems with the signals used as inputs. Clustering of the various types of disruptions using the geodesic distance on a Gaussian manifold allows the automated classification of the types of disruption with a confidence of the order of 85%. Therefore, the combined use of APODIS and this new classification is expected to provide early prediction and a good estimate of the type of incoming disruption to optimise the mitigation strategy. With regard to the manifold learning, linear and non linear tools have proved to be very useful to gain insight into the operational space and its boundary. The comparison of the dimensionality of the operational space of JET and AUG with PCA has shown great similarities. In particular, the first five principal components account for 90 % of the variances of both machines. The 2-D projections obtained with the SOM are particularly useful to visualize the behaviour of disruptive discharges. This is expected to help significantly in understanding the behaviour of the various types of disruptions and in developing predictors capable of extrapolating from one device to another.

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	JET offline classification	APODIS predictions
Safe	651	645
False alarms	n/a	6
Unintentional disruptive	305	300
Missed alarms	n/a	5
TOTAL	956	956
Intentional disruptive	35	n/a

Table I: Results of APODIS in real time during campaigns with the ITER like wall.

Greenwald Limit	(GWL)
Internal Transport Barrier	(ITB)
Current Rump-Up	(IP)
Density Control Problem	(IMC)
Low Density and Low 'q'	(LON)
Neo-Classical Tearing Mode	(NTM)
Impurity Control Problem	(NC)

Table II: Main disruption classes as defined by the experts.

Component	**AUG**		**JET**	
	Variance	**Cummulative variance (%)**	**Variance**	**Cummulative variance (%)**
1º	0.3692	36.924	0.433	43.2963
2º	0.1586	52.784	0.1829	61.5909
3º	0.1426	67.045	0.1462	76.2086
4º	0.1393	80.971	0.1237	88.5795
5º	0.1091	91.883	0.0552	94.0986
6º	0.0563	97.513	0.0335	97.4509
7º	0.0249	100	0.0255	100

Table III: Quantities used in the comparative analysis of JET and ASDEX Upgrade operational spaces.

Plasma parameters	Acronym	Unit (JET)	Unit (AUG)
Poloidal Beta	β_p	NA	NA
Safety factor of 95% of poloidal flux	q_{95}	NA	NA
Total radiated power/total input power	P_{frac}	NA	NA
Plasma internal inductance	li	NA	NA
Greenwald density/Greenwald limit	f_{GW}	NA	NA
Total input power	P_{tot}	W	W
Locked mode signal	LM	T	V

Table IV: Columns 2 and 4 report the variance retained by each component for AUG and JET respectively. Whereas, in columns 3 and 5 the cumulative variance is given for a progressive number of components

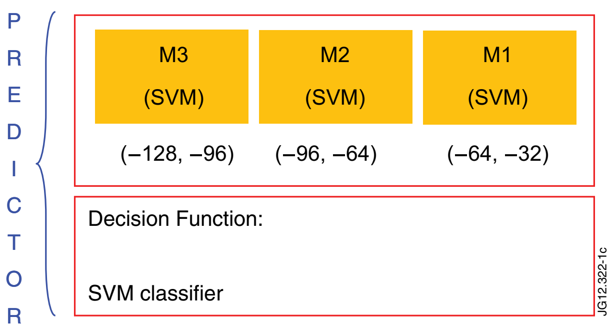

Figure 1: Architecture of the predictor APODIS. M1, M2 and M3 are three SVM classifiers analyzing three subsequent windows of data (times in ms). The decision function is implemented by an additional independent SVM.

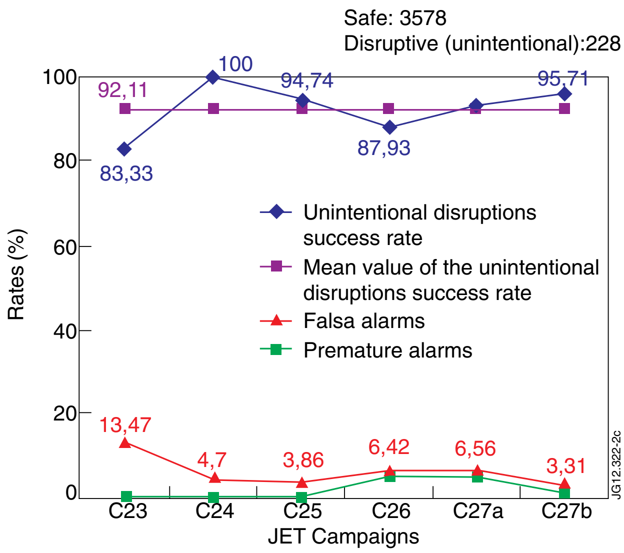

Figure 2: Success rate of APODIS for various JET campaigns with the Carbon wall in absolutely realistic real time conditions.

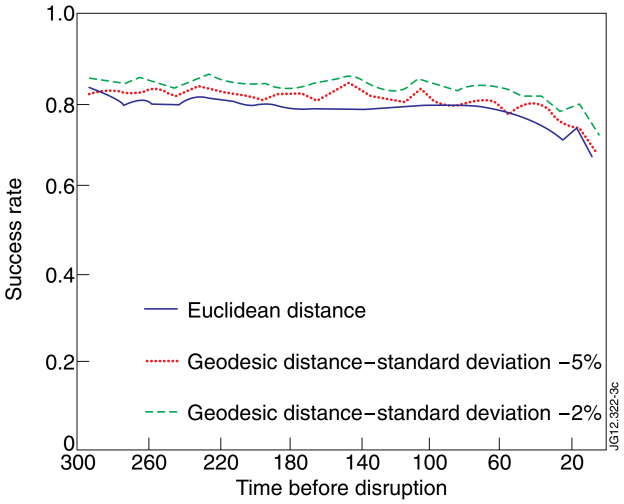

Figure 3: The overall success rate for the clustering based on the Euclidean and Geodesic distances.

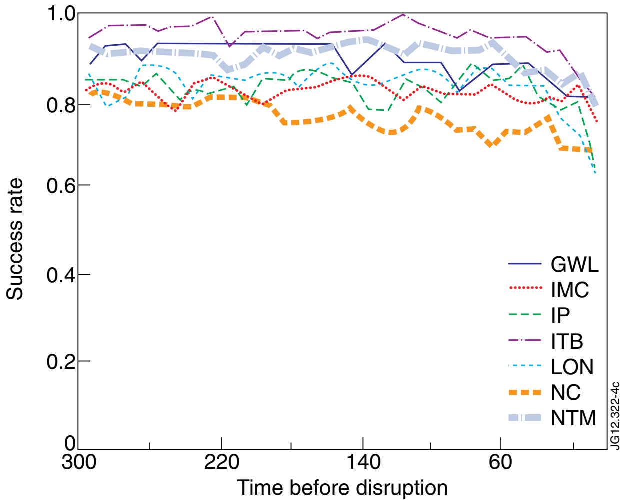

Figure 4: The success rate for the clustering based on the Euclidean and Geodesic distances particularized for the individual types of disruption.

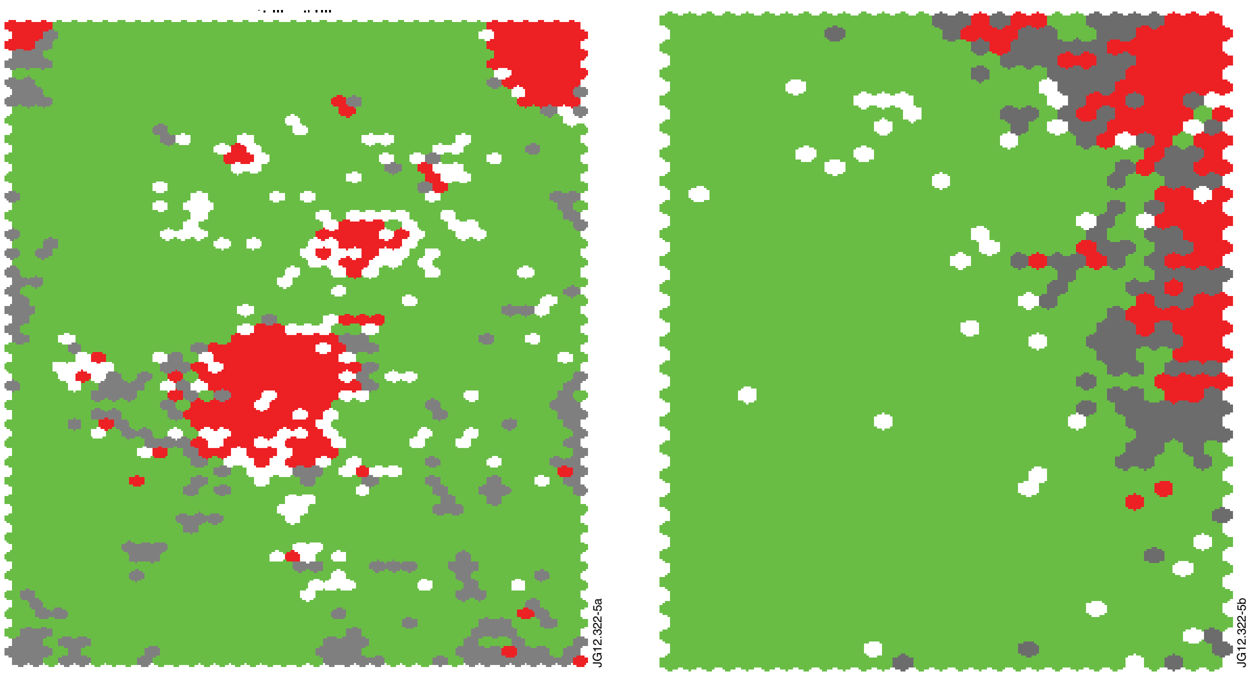

Figure 5 Top: SOM map of disruptive and safe discharges for JET: Bottom: SOM map of disruptive and safe discharges for AUG [11]. The colour code is: green safe clusters, red disruptive clusters, gray mixed clusters and white empty clusters. Both databases contain hundreds of thousands of points.