

Analysis of rotating mhd perturbations to identify disruptive phases in TCV tokamak

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The presence of rotating MHD instability is often a clue of unhealthy plasma conditions (e.g., large NTM Islands, or impurity accumulation, et cetera), which may justify the early and safe termination of a discharge. However, a similar approach would lead to terminate also discharges that can be recovered. The application of advanced RT processing, like Singular Value Decomposition (SVD), to MHD signals can provide additional information helpful, in principle, to disentangle such ambiguity.

In the present work, data are collected from 12 Mirnov coils in TCV, at 250ksps [1]. Before application of SVD, signals are filtered by a band pass (2-40kHz) filter and divided in time windows 1ms long, making up a matrix M 12x250 (Channels number per samples in a window). SVD decomposes the matrix M as the sum of (12) modes. Each SVD mode is characterized by its strength (the singular value, SV), its time behavior (Kronos), and its spatial footprint (Topos) [2]. SVD modes (i.e., a triplet of associated SV, Topos and Kronos) are ordered with respect to the strength of the mode (higher SVs first). In the present work, simple post-processing are applied to SVD results to provide up to 24 variables, which give a detailed description of the behavior of the most important modes and of the whole MHD fluctuations state. The 24 variables are then filtered with 16 samples boxcar, and returned with a 2ms sampling.

Data were collected for 196 safe discharges and for 82 disruptions, performed at TCV in 2015-2017 campaigns. The above processing has been applied in the flat top phase for safe discharges, while in case of disruptions the interval from the start of the flat top to the disruption has been taken into account.

In order to investigate the information contents of the "MHD state" about disruptions, three different approaches are applied to the database and compared here.

Firstly, a disruption alarm is defined on the basis of the MHD strength, then using only two out of 24 variables of SVD: H and DH . H is the Shannon's entropy applied to the singular

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values from each SVD time window, and is a measure of the strength and the coherence of the mode. DH is the Kullback-Leigler divergence applied to adjacent SVs profiles, and provides a measure on the persistency of the mode. Lower values of H indicate stronger MHD modes, while low DH values indicate persistent or saturated modes. In the H-DH plan, "disruption" points cover almost the same area of the "safe" ones but there exist regions populated by D-points only for lower H values but quite higher DH values.

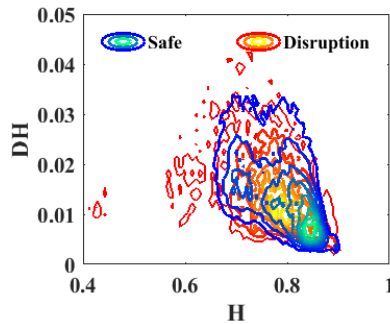


Figure 1 a) Density map of disruptive and safe samples in the H-DH plan.

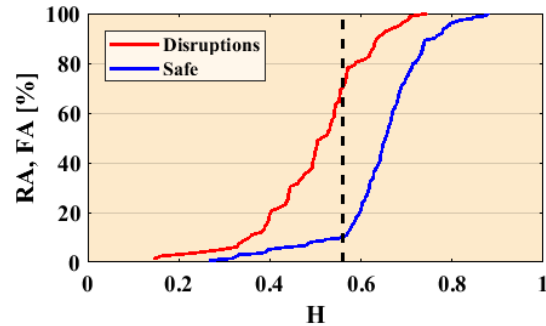


Figure 1 b) Statistics (per pulse) on minimum H values. Posing a lower threshold of 0,56 on H, 70% of disruptions are recognized (RA), and alarm is triggered only for the 10% of the safe discharges (FA).

These results suggests that in TCV MHD preceding a disruption is typically strong and fast evolving (growing) in a time scale of ~ 16 ms. The variable H is then the most significant here and posing a lower threshold (~ 0.56) on it, as shown in Figure 1b, an alarm is defined which anticipates the current quench of (0-162)ms for the 70% of the disruptions - anticipation time is almost uniformly distributed, but in 9 out of 57 disruptions it is triggered also with larger anticipation (up to 1s)-, and only for the 10% of safe discharges. In the second approach the contribution provided by other SVD features (24) is investigated with the help of a Principal Component Analysis (PCA). In PCA, Principal Components (PC) are the linear combination of different variables which maximize the variance of the whole dataset. Also in this case, PCs are returned ordered descending with the partial variance. Figure 2a) shows the Pareto diagram for the first 10PCs, which explain $>95\%$ of the whole data variance.

The Mahalanobis distance in the first three PCs space (which explain the 80% of the whole data variance) from the set of safe points is calculated. Posing a threshold ($d_s=11$) on this measure, a disruption alarm is defined which performs RA of 84%; FA, 15%; and anticipation time (t_A) of 250ms(± 150 ms).

First three PCs mainly depend (see Fig. 2b) on variables related with the strength of the MHD (H, ILSV, SVQ1), and also on variables describing the mode frequency estimates

(FP and FX) and standard deviations (STP and STX) for the two first Kronos calculated by SVD.

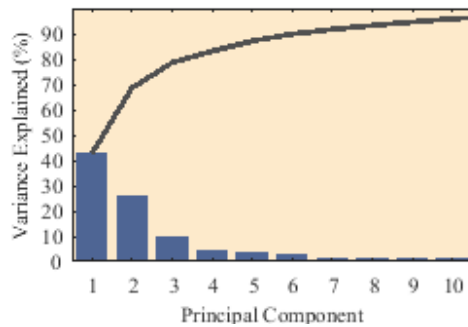


Figure 2 a) Pareto diagram for the first 10 PCs.

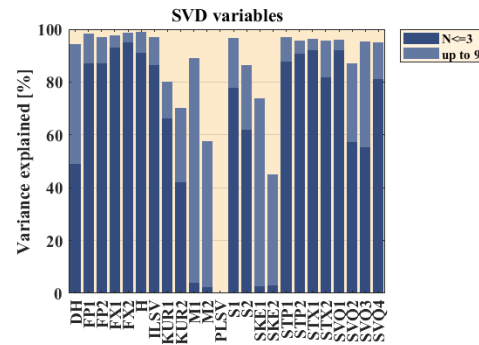


Figure 2 b) Relative variance of each SVD variable explained by the first three components.

Finally, the Generative Topographic Mapping (GTM) [3,4] is applied to the PCA results to optimize the number of PCs capable of discriminating the disruptive behavior. GTM is an advanced manifold learning algorithm that computes a mapping from a low dimensional (2D) latent space into the high dimensional data space through Radial Basis Functions (RBFs). This allows comparing the resulting mapping in the 2D latent space of datasets with different dimensions (the number of PC taken into account). In order to build the training dataset for GTM, points from disruption discharges (*D-points*) are taken from tA, as evaluated in the previous approach; while points from safe termination discharges (*S-points*) are randomly selected to preserve the statistical distribution of each variable. After this selection, training dataset results of $\sim 2 \times 8000$ points. In Figure 3a is reported the percentage of latent points corresponding only to disruption clusters in the data space ($D[\%]$), for different latent grids, from 29×29 to 35×35 , and for different number of PCs, from 3 to 10. Figure 3a shows that varying the grid $D[\%]$ is always maximized using the first 9 PCs. The variance explained by the first 9 PC for each SVD variable is reported in (Fig.2b), with respect to the previous case variables related with the persistence (DH) of the mode and the dynamic in the SVD time window (M and KUR, first and third moment of the Kronos, respectively) play here a role, i.e. the variables which are more capable to discriminate between a saturated mode or a growing/damping one.

The GTM parameters are then optimized for 9 PCs aiming at a smooth mapping, i.e., minimizing the number of latent points not covered by any point in the database. The optimized map in Figure 3 b) is used to evaluate the class memberships (safe or disruption) for each pulse.

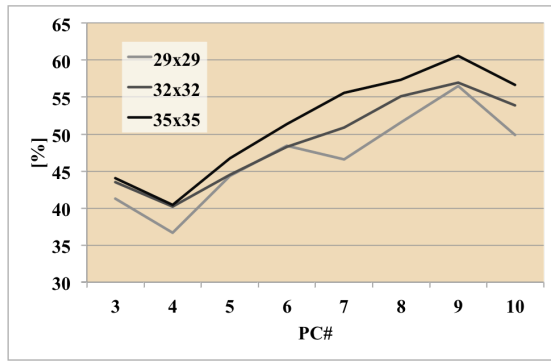


Figure 3 a) Percentage of disruptive points discriminated by GTM for a different number of PC and different size of the GTM grid.

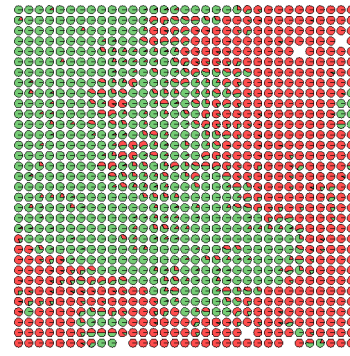


Figure 3 b) GTM map obtained by 9PC and optimized hyper-parameters. *S-points* and *D-points* are discriminated at 58% and at 62%, respectively, and overlap for <40% of the map.

However, the analysis of the representation of each PC in the latent plane of Figure 3b highlighted that the first three PCs have a smooth distribution resembling to some extent the distinction on the map between the two classes. Nevertheless, the following PCs, as in particular the fourth one, are quite "noisy" and much less correlated to the intrinsic structure characterizing the two classes.

Conclusions. Application of SVD and PCA gave rise to preliminary very encouraging results, as already found for other machines [5], and in the present case highlighted the importance of variables strictly related with the strength of the MHD mode and its frequency. The application of GTM confirmed that the most important contribution to discriminate between disruptive and safe discharges is provided by the first three PCs and related MHD features. The GTM mapping of SVD results is quite challenging and further work needs to be done for exploiting more consistently the information associated to these MHD indicators and for their integration in more complex schemes including other discriminative physics quantities.

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