

# Wavelet analysis of Mirnov coils signals for disruption prediction at JET

*B. Cannas<sup>1</sup>, S. Carcangiu<sup>1</sup>, A. Fanni<sup>1</sup>, A. Murari<sup>2</sup>, A. Pau<sup>1</sup>, G. Sias<sup>1</sup>, P. Sparapani<sup>1</sup>, and the JET contributors<sup>3</sup>*

<sup>1</sup>*Electrical and Electronic Engineering Dept. - University of Cagliari, Italy*

<sup>2</sup>*Consorzio RFX, Corso Stati Uniti 4, 35127*

<sup>3</sup>*See the Appendix of Romanelli F. et al 2014 Proc. of the 25th IAEA Fusion Energy Conf. (St. Petersburg, 13 Oct)*

*\* See X. Litaudon et al. Nucl. Fusion 57, 102001*

## I. Introduction

Disruption are often preceded by oscillating MHD modes slowing down, growing and locking when the amplitude exceeds a critical value. The fluctuations of the poloidal magnetic field recorded by the Mirnov coils could provide useful markers related to the presence of this kind of instabilities causing disruptions. This paper proposes a time-frequency analysis of the Mirnov signals recorded at JET by the high resolution probes of KC1M diagnostic. The work is a contribution toward the definition of new features characterizing disruptive behaviours to be used as input in a multisignal disruption predictor.

Mirnov coil signals are non-stationary signals. Spectral analysis using the Fourier Transform is a powerful technique for stationary time series where the characteristics of the signal do not change with time. For non-stationary time series, the spectral content changes with time and hence time-averaged amplitude spectrum found by using Fourier Transform is inadequate to track the changes in the signal. Compared to Fourier analysis, wavelet analysis is a step forward in the spectral characterization of a time series, since allows to study the temporal evolution of amplitude, frequency over time scales comparable with the wave period [1]. The continuous wavelet transform of a discrete time series  $\{x[i]\}$ , sampled at the rate  $t_s$ , is defined as the convolution product of  $\{x[i]\}$  with a scaled ( $t \rightarrow t/s$ ) and shifted ( $t \rightarrow t - \tau$ ) version of a mother wavelet  $\psi(t)$ . The windowing is intrinsic in the wavelet transform and it depends on scale  $s$ . The smaller the scale factor, the more compressed the wavelet is, so it can catch rapidly changing details in the signal.

The database for this study consists of 110 non disruptive pulses and 114 disruptive pulses selected from the ITER Like Wall (ILW) experimental campaigns performed at JET from 2011 to 2013. The Mirnov signals have been acquired at the frequency of 2 MHz, and

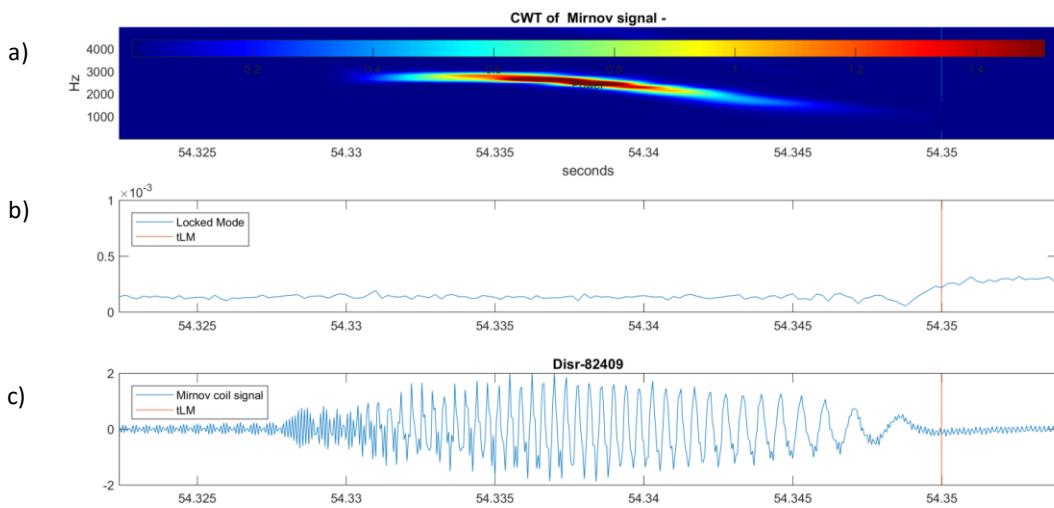
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resampled at 20 kHz. Then, the wavelet coefficients are evaluated on a mobile window in order to simulate a real time application.

## II. Stand Alone Mirnov Coil Disruption predictor

In order to test the performance of the Continuous Wavelets Coefficients (CWT) as disruption predictor, the data base has been split into about 60% for the training and 40% for the test sets. Figure 1-a reports the CWT of a Mirnov signal of the disrupted discharge 82409. Note that each wavelet is a (Nfreq×Nt-sample) matrix where Nfreq is the number of frequency components and Nt-sample is the number of time samples. Fig. 1-b reports the Locked Mode (LM) signal and Fig 1-c the Mirnov signal clearly showing the locking of the mode.



**Figure 1 - a) CWT coefficients b) LM signal (LM alarm in red) c) Mirnov coil signal**

A threshold on CWT low frequency coefficients was chosen optimising the performance in terms of false alarms and missed alarms on the training set. The results of the analysis performed on this single probe show that, as expected, the CWT indicator performs many false alarms (3 and 10 on training and test set respectively) even if it misses 21 disruptions on the training set and 9 on the test set.

## III. CWT of the Mirnov Coils as an input of a disruption predictor based on GTM

In [3], it has been shown how a low dimensional map of a high dimensional plasma operational space can be successfully used for disruption prediction and avoidance. In particular, a Generative Topographic Mapping algorithm [4] has been used to map the seven dimensional operational space of JET, where the parameters synthesize both spatial/temporal quantities describing the spatial distribution of the main kinetic quantities, such as current, temperature, electron density, and radiation profiles, or are global zero-dimensional quantities. Figure 2-a reports the resulting 2-D GTM, which is colored on the basis of the node composition: green

clusters contains samples from non disruptive discharges, whereas red clusters refers to the unstable phases of the disrupted discharges. Grey clusters contain both non-disruptive and disruptive samples. The white clusters are empty. The temporal evolution of the operative point during the flat top of a discharge can be projected on the map and a class membership can be defined as a function of time (see Fig. 2-b) that reflects the probability of belonging to one of the two classes. Following the trajectory of the discharge on the map it is possible to link the disruption risk of the clusters to the percentage of disrupted samples into the clusters. A viable disruption prediction system can be based on the fulfilment of several criteria based on both the answer of the GTM and the exceeding of thresholds on single signals, such as the LM signal. In Fig. 2-c, the multiple criteria AND/OR logic alarm scheme proposed in [3] is shown (in black), where the condition derived from the GTM model is that an alarm is triggered when the trajectory stays in a disruptive or a mixed cluster containing at least  $DS\%$  disruptive samples for at least  $d$  consecutive samples. Only one disruption has been predicted less than 10 ms from the disruption time, and only one false has been obtained in a test set independent from the training set, and with warning times suitable for avoidance purposes. The use of the LM allowed to limit possible tardy or missed alarms due to disruptive processes characterized by fast time scales, or false alarms due to transients. In the present proposal, the alarm scheme is integrated with a further criterion based on the CWT of the Mirnov coils (in red in the schema of Fig. 2-c) in order to possibly anticipate the LM alarm. One more false alarm has been produced on the test set, but in 12 cases the disruption is predicted in advance.

Figure 3 shows example of alarm trigger anticipated by CWT indicator for the pulse 83545. The Mirnov signal is shown in Fig. 3-a, the LM in Fig. 3-b and one the wavelet coefficients in Fig. 3-c. As it can be noticed, the CWT indicator triggers the alarm (dotted black line) during the growth of the low frequency mode, well in advance with respect to the locking of the mode.

## References

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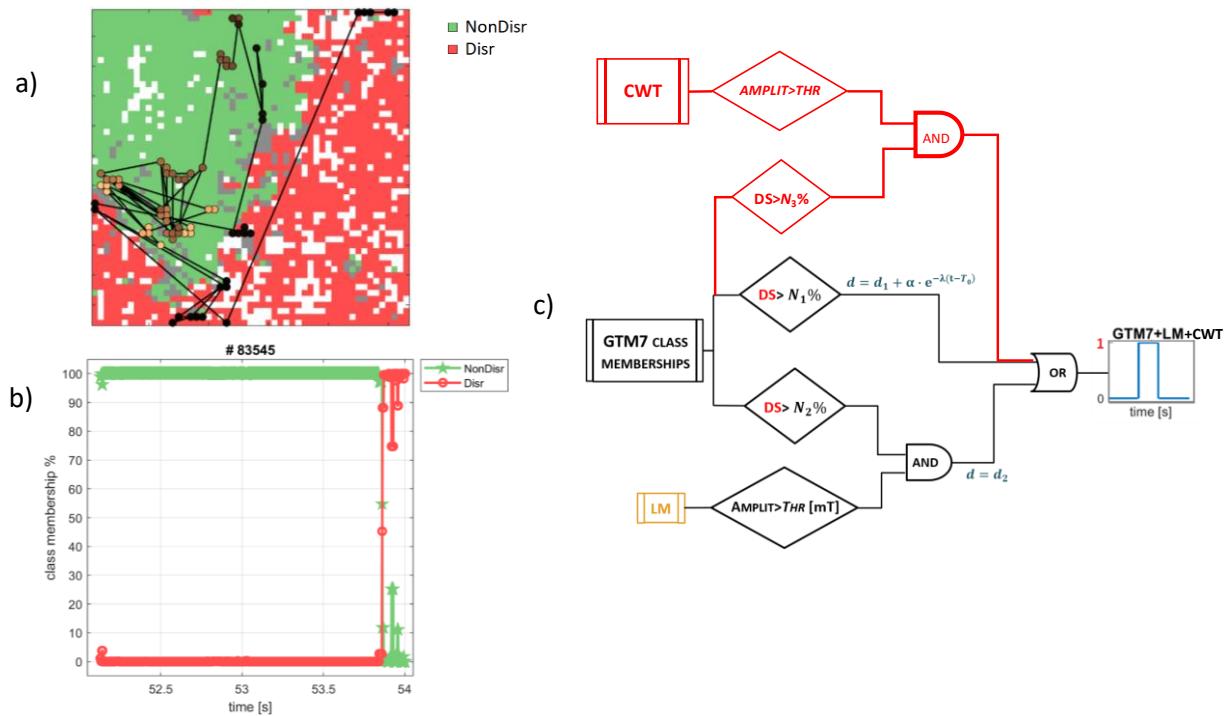


Figure 2 – a) GTM of the 7 JET plasma parameters. On the map the trajectory of disrupted discharge # 83545 (black line); b) Class member functions of non-disrupted (green) and disrupted (red) classes; c) Multiple criteria alarm schema.

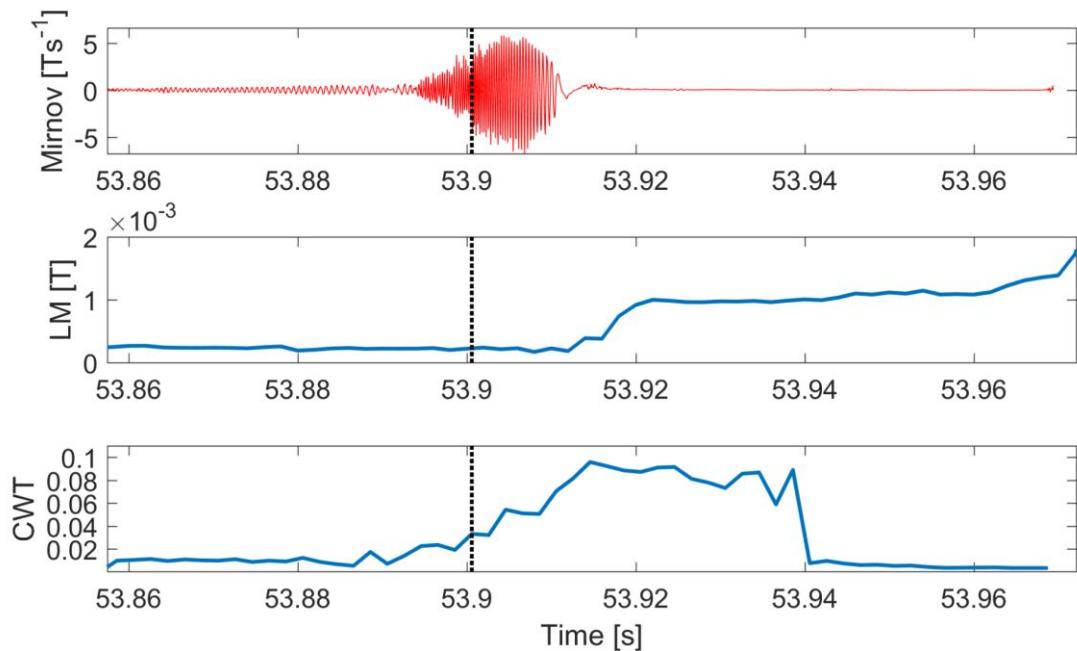


Fig. 3 - Alarm anticipated by CWT indicator for pulse 83545 a) Mirnov signal b) Locked Mode c) wavelet coefficient