Real-time recognition of plasma confinement states in TCV and transfer learning to JET using ML models

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Abstract

Fusion plasmas in Tokamaks can be categorized as being in mainly low (L) or high (H) confinement states, with the possibility to be in an intermediate state referred to as "dithering" (D). We present two machine lerning (ML) models for the automatic recognition of plasma states: a real-time capable one based on a ConvLSTM [1] architecture and another based on UTime [2] aiming to operate offline and so serving as a high-accuracy baseline for automatic data labelling of confinement states. We benchmark the UTime and ConvLSTM models in terms of generalization capabilities from TCV to JET and improve the extrapolation significantly by resampling and detrending the input signals. We show first results on the real-time implementation of the ConvLSTM in the TCV control system [3] and highlight the importance in combining physics- and ML-based detectors for the robustness of the predictions, focusing in high density limit experiments.

Introduction

In general, Tokamak plasmas can be described usually as being either in three main confinement states: low (L), dithering (D) or high confinement (H) modes. To keep plasma performance, the plasma control system (PCS) has to react differently if the plasma is in L, D, or H mode. At the same time, it is important to detect loss of confinement, since it can often be related to the onset of specific disruption paths, e.g H-mode degradation in high density limit (HDL) experiments. The development of real-time (RT) capable models for the automatic detection of these states is a crucial component for the success of future large scale devices such as ITER and present DEMO designs to enhance the control of plasmas at the highest attainable density and confinement, optimizing therefore the energy gain. Besides, accurate models are important to automatize the data labelling aimed at confinement transition studies currently done by experts, which is a time consuming process. The automatic and consistent labelling of databases (DBs) is needed to perform a plethora of analyses, interpretate experiments and model validation.

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We present new studies using two data-driven machine learning (ML) models, ConvLSTM [1] and UTime [2], which have been demonstrated to be successful for confinement state detection, being able to operate close to human-level precision. We present for the first time RT results of the ConvLSTM in the TCV PCS and show how a combination between ML and physics-based detectors can serve the control of HDL experiments. Finally, we evaluate the ConvLSTM and UTime generalization from TCV to JET and show that accurate scores can be achieved if proper care is taken to pre-treat the input signals by resampling and detrending.

Database preparation

Two main diagnostics were used which are sensitive to the different confinement states. A photodiode (PD) which measures the line-integrated emitted radiation and the far infra-red interferometer (FIR) which is proportional to the line integrated electron density along a line of sight of the Tokamak. They are used in most of the existing Tokamaks and will also be available in ITER. This results in a good choice for the cross-machine studies. Besides, they are available in RT (for TCV) and do not depend on computationally expensive plasma equilibrium reconstruction, which gives more flexibility. Despite that the PD in TCV has an H_α filter, while the used in this work in JET measures radiation from Beryllium, the dynamics of the plasma captured by the PD was shown to be similar in both devices. In contrast to previous works [1, 2], which relied on PD, FIR, diamagnetic loop (DML) and plasma current (I_p), we limited our studies to use the PD and FIR, since the DML and I_p did not improve the ML models precision.

Fig. 1 shows the different steps followed to build the DBs to train the models. The extracted signals from the PD and FIR diagnostics were resampled from 50 kHz to 10(5) kHz in TCV(JET). The PD in TCV consists of 14 channels looking at different plasma locations. The channel pointing closest to the X-point was selected as input due to its higher sensitivity with respect to the other channels. The signals were scaled by a mean value for the ConvLSTM and on a shot-by-shot basis for the UTime model. Dynamic Time Warping + Clustering (DTW-HC) algorithm was used to cover as exhaustively as possible the state space of plasma confinement in TCV and JET. Finally a multi-machine interface [5] was used to label the selected shots.

Real-time results in TCV

The ConvLSTM was embedded in the RT supervisory control of TCV called SAMONE [3]. It has an execution rate of 0.04 ms with 0.1 ms of delay. Fig. 2 shows the evolution of a TCV HDL discharge in terms of the $H_{98y,2}$ confinement factor and the electron edge critical density $n_{\text{e-edge-crit}}$ [4] (left), the boundary in black denotes the empirical disruption limit. The plot in the right shows the evolution of the distance (top panel) between the system states ($H_{98y,2}$;

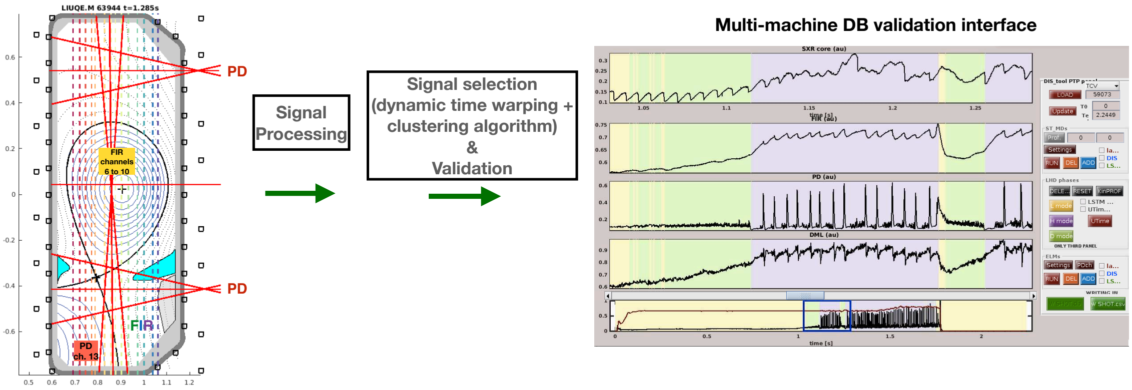

Figure 1: *DB preparation. Left to right: Diagnostics placement in the TCV Tokamak, signal processing which consists in resampling, channel selection and normalization, DTW-HC algorithm to select a representative state space in TCV and JET, multi-machine interface to validate the selected shots [5].*

$n_{\text{e-edge-crit}}$) and the disruption limit for both online and offline computations. The mid panel shows the ConvLSTM predictions for L (1), D (2) and H (3). The last panel are the actuator responses, neutral beam injection (NBI) and gas valve injection (GAS) used for plasma heating and density control. It can be seen that the ConvLSTM predictions are well correlated with the offline distance computation where $d > d_{\text{crit}}$, $d \sim d_{\text{crit}}$, $d < d_{\text{crit}}$ correspond to H, D and L respectively. Additionally, for this particular discharge the online distance did not match the offline, this was because FIR measurements were affected by *fringe-jumps* and the error was propagated to the distance computation. Thanks to the ML-based detector, which detected the first HDL transition, the PCS could react properly, freezing the gas at $t \sim 1.15$s at the HD transition. This shows the importance on relying on a combination of independent detectors for the robustness of the predictions.

Transfer learning from TCV to JET

Transfer learning techniques can be exploited to test ability of confinement detector to extrapolate to new devices for which no data exists yet, e.g ITER. For this, we selected a set of TCV discharges that were most similar in terms of DTW distance to JET. Next, a baseline model was trained in the selected TCV set and evaluated directly in JET. The analysis was limited only to L and H modes. The accuracy was evaluated in terms of the Cohen's Kappa-statistic (κ), which measures the agreement between the ground truth and the model predictions [2]. To improve the generalization capabilities and take into account the different confinement time-scales between the two devices, the signals in JET were resampled such that a typical length of a shot in JET ($\sim$20s) matched a TCV one ($\sim$2s). For 10 kHz TCV signals, this resulted to be $\sim$ 1.6 kHz in JET. We have found also that by detrending the PD signals the generalization improved signifi-

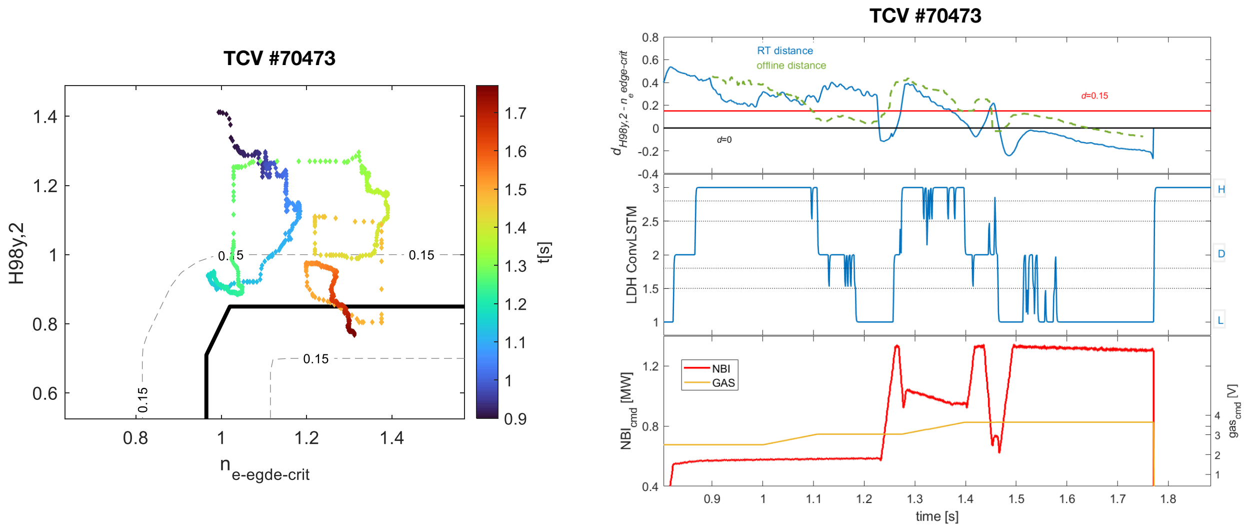

Figure 2: *Evolution of a TCV HDL discharge in the confinement phase-space (left) and distance to the disruptive boundary, ConvLSTM predictions and actuators (1st, 2nd and 3rd panels in the right).*

cantly, attaining a score of $\kappa = 0.78$ and $\kappa = 0.86$ for the ConvLSTM and UTime respectively, comparing to the scores $\kappa = 0.27$ and $\kappa = 0.63$ obtained without signal detrending.

Conclusions

Two ML models (ConvLSTM and UTime) were presented for the automatic detection of plasma confinement states in TCV and JET Tokamaks. First RT results were shown in TCV with the ConvLSTM, showing its application in the control of a HDL experiment and demonstrating the importance of relying on a combination between physics- and ML-based detectors in terms of robustness. Finally, preliminary studies on the extrapolation from TCV to JET have shown promising results using signal resampling and detrending. As next steps, transfer learning from smaller to larger devices will be studied more in detail, adding domain adaptation techniques and data from the AUG Tokamak. We will also aim to find physics rules based on confinement time-scales for a more machine-independent representation.

References

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