# Detection of plasma confinement states in the TCV tokamak

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## Abstract

Fusion plasmas in Tokamak machines can be categorized as being in three different confinement states: low (L), high (H) and dithering (D). These regimes are characterized by different transport properties of the plasma affecting the energy confinement, which reflect in characteristic physics behaviours of the plasma dynamics. Current devices, and also future reactors as ITER and DEMO, rely on the H mode to achieve high performance close to operational limits which is desirable in terms of power balance. The development of data-driven, real-time qualified, approaches to automatically detect the occurrence of transitions between these confinement states is essential to find for these machines the highest attainable density and confinement, and provide enhanced capability for controlling Tokamaks, such as safe discharge termination, and to optimize the energy gain. For this, reliable and large databases labeled by experts are needed to train the aforementioned algorithms. We propose two algorithms, a sequence to sequence model (seq2seq), capable of running close to real-time, and a segment classifier based on the UNet architecture (UTime), which although not real-time capable, can look at a larger context serving as a baseline, more adequate model to help on the labelling process.

## 1 Introduction

Despite the complex, highly non-linear, plasma physics phenomena present in current Tokamak fusion devices, such as particle transport, turbulence and magnetohydrodynamic instabilities, a plasma can be described in general terms as being in one of three *confinement states*: low-confinement (L),

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high-confinement (H) or dithering (D) modes. It is well known within the fusion community that accessing and maintaining plasmas in H mode is one of the keys to optimize energy gain, and is an essential component in developing economical nuclear fusion reactors. Furthermore, it is particularly important for the control system of the machine, to know the moment when the H-L back transition occurs in the ramp-down phase of a fusion discharge, where *disruptions* (a sudden and uncontrolled loss of the plasma current and confinement) are more prone to happen, potentially damaging the plasma facing components of the machine. Hence, the automatic detection of these regimes in real-time is crucial for the success of future large scale devices such as ITER and DEMO.

Previous work based on deep learning, namely with a CNN-LSTM has shown promising results on this task [1]. However, performance were limited by the quality and size of the database. Besides, a vanilla RNN is unable to produce decisions over sequences of outputs, more as a human expert would do, and is constrained to have the same prediction resolution as the input labels, which might be unrealistic.

To face the aforementioned issues, we propose two algorithms both with an encoder-decoder structure, a sequence to sequence model (seq2seq) and a segment classifier based on the UNet architecture (UTime). Both models are able to handle different input-output resolutions. In addition, seq2seq models, as well as associated mechanisms such as attention [2, 3, 4], have considerably advanced the field of neural machine translation and transduction in the past few years. On the other hand, an UTime architecture has shown remarkable results in segmenting complex time-series data as sleep staging in a human brain [5]. Contrary to UTime, the seq2seq model is capable of running close to real-time and so it could be integrated in the control system of current and future devices, whereas the UTime is a multi-scale convolutional architecture which can look at larger context serving as a baseline more suitable model to help on the time consuming labelling process.

## 2 Methods

### 2.1 Database preparation

We have assembled a dataset based on the time-traces of four TCV diagnostics that experimentalists use to determine, in post-shot analysis, the state of the plasma. These are the *photodiode signal* (PD), which measures line emission from impurities with a $D_\alpha$ filter (656.3 nm). The *interferometer signal* (FIR), measures the line-integrated electron density in the plasma. The *diamagnetic loop* (DML), refers to the measurement of the total toroidal magnetic flux of the plasma and the *plasma current* (IP) which is the reconstructed toroidal plasma current. The 4 different signals used for this work were resampled to the same frequency of 10kHz. Since each TCV discharge is usually up to 2s long, this means that our shot signal data consisted of 4-channel time-series of about 20000 time slices each. Each signal were normalized by its mean across the whole shot.

The selection of the discharges for training and testing was done in order to cover as exhaustively as possible the state space of the plasma confinement states in TCV, accounting for the different temporal evolutions of the plasma. Using a Dynamic Time Warping algorithm we measured the similarity between pairs of temporal sequences and associated them to a given group, based on a similarity measure. The desired number of groups was obtained by applying a Hierarchical Clustering algorithm to univariate time sequences corresponding to the entire plasma discharges. From each of the clusters, shots were extracted and classified as an (not)interesting shot from the physics point of view (i.e the presence of L/D/H transitions). Some clusters were discarded since they consisted of disruptions or technical issues without achieving an H mode confinement state or a stationary phase. Limiting to the interesting shots and maximizing the number of clusters where a given shot arose from, discharges were selected for further validation (ground truth determination). For the latter, a consensus on a common convention between two experts was established to determine the label of each time step for all shots. The outcome was an unique, consistent, ground truth per shot. A test set to evaluate the final results of the model was carefully determined and fixed during all the experiments. Although the test set was selected to be similar to the train-val set, we chose a few shots that were particularly challenging, since we were interested in testing the network in a more pessimistic scenario. Figure 1 shows how a typical TCV discharge looks like. The four signals are displayed together with the plasma state class corresponded to each region.

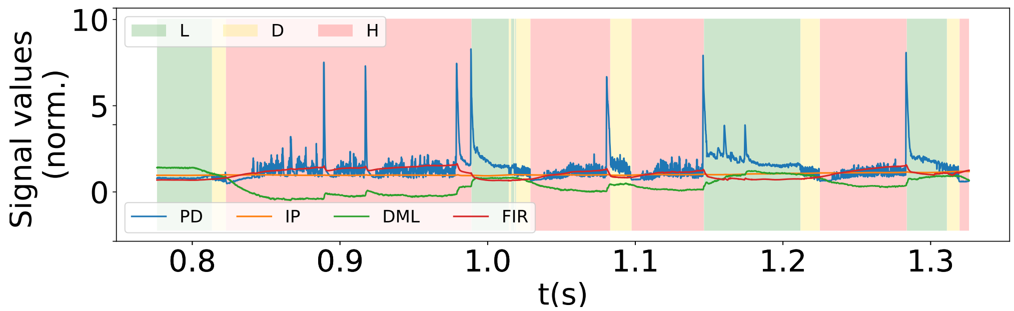


Figure 1: TCV shot $\#61714$ from $t = 0.8s$ to $t = 1.3s$. The 4 signals used are shown: the photodiode (PD), plasma current (IP), diamagnetic loop (DML) and the interferometer (FIR). Overlayed in green, yellow and red are the labels Low (L), Dither (D) and High (H) corresponding to different states of the plasma.

### 2.2 Evaluation metrics

To compare the models' predictions with the ground truth, we used the Cohen's Kappa-statistic ($\kappa$), which measures the agreement between two sets of categorical data [6]:

$$\kappa = \frac{p_0 - p_e}{1 - p_e} \tag{1}$$

where $p_0$ denotes the actual relative agreement between the two sets (identical to accuracy), and $p_e$ denotes the probability of the two sets randomly agreeing with each other, defined as $p_e = \frac{1}{N^2}\sum_k n_{k1}n_{k2}$, where $k$ are the categories (in our case $k = 3$), $N$ the amount of observations (number of time instants of the sequence), and $n_{ki}$ the number of times set $i$ (e.g ground truth or model prediction) predicted category $k$. Generically, the $\kappa$ values oscillate between 0 and 1, the former (latter) indicating poor (perfect) performance respectively, and it can also be negative indicating an agreement worse than random.

### 2.3 UTime implementation

The UTime architecture was inspired by the previous work applied to sleep stages segmentation [5]. It inherits the properties of U-Net but for 1D time-series segmentation. As such, it can receive the whole signal as input and make predictions of its labels in a single forward pass. Let $x \in \mathbb{R}^{TS \times C}$ where $T \sim 2$s is the duration of the signal, $S$ the sampling frequency and $C$ the number of channels (PD, FIR, DML and IP). The UTime maps, via an encoder - decoder followed by a segment classifier, $x$ to a vector $v \in \mathbb{R}^{T \times e}$ where $e$ is the desired output frequency of the segmentation. In our case, we relied on a dense ground truth, where a label was assigned at each time step, and so we used $S = e = 10$kHz. Nevertheless, $e$ remains arbitrary and another value $S \neq e$ could have been chosen. See [5] for further details on the UTime structure.

To account for class imbalance of our sequence data, specifically for the D mode, we used the generalized dice with uniform class weights as a cost function [7]. Besides, during training we randomly sampled sub-sequences on-the-fly in batches. Each sub-sequence was chosen in such a way that the class label belonging to its first time step is balanced within the batch.

Contrary to the previous UTime implementation on sleep stages [5], we found neither dilated filters nor the use of several MaxPooling layers (deeper architecture) beneficial. These features can provide a large receptive field (RF) at the last convolution layer of the encoder [8]. However, it has been shown that the use of very large RF can harm performance if the regions of interest for the segmentation are characterized by much smaller time scales [9]. We opted for an architecture with a RF comparable with the typical length of our plasma states. We found dropout regularization after MaxPooling layers useful. A diagram of the network architectures (UTime and seq2seq models) can be found in Figure 2 in the Appendix. The code is publicly available at `https://github.com/gmarceca/UTime-Plasma-States`.

### 2.4 Seq2seq implementation

We used an encoder-decoder sequence to sequence model with attention, with an architecture similar to that proposed by [3], though with some modifications. Firstly, in most cases with seq2seq models, one has the entire source sequence for the encoder to process. In our setting, due to the real-time environment of a fusion experiment, only the inputs (signal values) up to a certain point in time are known. Therefore, the encoder is fed with consecutive sub-sequences of the input as they become available, and not with entire shot sequences. In addition, our encoder is a convolutional LSTM; we used this architecture because our expectation is that both local and long-term correlations exist in the data. The convolutions are 1-dimensional, and have 4 channels, to account for the different signals. Each sub-sequence (input) is fed to the encoder as a series of overlapping windows, which are processed by the convolutions; the output of the convolutions is processed by the LSTM. The sub-sequences have a total size of 300 source timesteps; the windows have $40$ timesteps, and we used a stride of 10 between successive windows.

The decoder consists in an LSTM and an attention layer. We used the decoder architecture with the general form for computing the alignment weights of the attention layer. The decoder receives the context vectors produced by the encoder for each new sub-sequence drawn from the input data, and is trained to approximate the joint probability distribution of plasma confinement states $p(z|x)$, where $x$ is the signal data from a shot and $z$ the label to represent the state of the plasma. To account for labeling noise, and the varying time scales of the transitions between plasma modes, we reduced the temporal resolution of the outputs (with respect to the inputs) by a factor of 10. Finally, we used a beam search algorithm to find samples of $z$ with high probability from $p(z|x)$. We defined the beam search to have a maximum of 20 beams. The implementation of this model can be found in `https://github.com/frdmat/event-detection/blob/main/code/tf_seq_to_seq.py`.

## 3 Results

The $\kappa$ score results obtained by the two models are depicted in Table 1 for training, cross-validation (CV) and test sets. They were computed on a per-state (L, D and H) basis, where a single score has been obtained by evaluating Equation 1 in a sequence resulting from the concatenation of all shots belonging to each set. Also, a weighted average mean across the three plasma states was calculated, where the weight was defined as the relative frequency of each class in the whole sequence. The source labels were downsampled, by the maximum class present in a window, to the same temporal resolution as the model's output (from 10kHz to 1 kHz) from which the $\kappa$ score was finally evaluated.

As expected, due to the heterogeneity of dithering behaviours, all models reached higher accuracy for L and H modes than D mode. A $\kappa$ score of 0.94 and 0.96 was obtained for L and H mode respectively in the whole test set for the seq2seq and UTime models. For the D mode the $\kappa$ was 0.86 and 0.89 for both models respectively. These results represent an improvement of $\sim 10\%$ for the three states with respect to [1], as shown in the first row in the table. Given that the previous studies where computed in a different (reduced) dataset, we evaluated the previous CNN-LSTM model in the current dataset (shown in the 2nd row) to evaluate the contribution due to the dataset update. Although the new dataset significantly improved the results of the CNN-LSTM model with respect to the previous one, we can see that the seq2seq and UTime models are still more accurate (in particular for the D state), which correspond to an improvement due to the models itself. It is worth to remark the difference in the $\kappa$ score, in particular for L and H modes, obtained between the CV and test sets. As mentioned in 2, the test set was built with the presence of particularly difficult examples, and we can see this reflected in the CV results compared with the test set, in particular for L and H modes.

## Conclusions

We developed two models based on an encoder-decoder structure to automatically detect the confinement state of a plasma during a TCV discharge. A seq2seq model, able to run close to real-time and an UTime model, which processes the whole signal at once and is able to look at a larger context. Both models have shown to be very accurate regarding the recognition of the plasma states L, H and D modes, achieving a $\kappa$ score of 0.94, 0.96 and 0.89 respectively. These results exceed by $\sim 10\%$ the ones obtained in previous studies [1]. Furthermore, both architectures rely on $\sim 10^5$ trainable parameters which is $\mathcal{O}(10)$ lower than the previous CNN-LSTM architecture. Although UTime has

Table 1: $\kappa$-statistic scores for each plasma mode and as a mean, on training, 5-fold CV and test data. If not specified, the models where evaluated in the current dataset.

| $\kappa$ scores | | L | D | H | Mean |
|---|---|---|---|---|---|
| CNN-LSTM (dataset [1]) | Train | 0.96 | 0.89 | 0.97 | 0.96 |
| | Test | 0.82 | 0.77 | 0.85 | 0.83 |
| CNN-LSTM | Train | 0.98 | 0.91 | 0.98 | 0.98 |
| | Test | 0.92 | 0.78 | 0.91 | 0.90 |
| seq2seq | Train | 0.99 | 0.99 | 0.99 | 0.99 |
| | 5-CV | $0.97 \pm 0.01$ | $0.89 \pm 0.03$ | $0.98 \pm 0.01$ | $0.97 \pm 0.01$ |
| | **Test** | **0.94** | **0.86** | **0.96** | **0.94** |
| UTime | Train | 0.99 | 0.98 | 0.99 | 0.99 |
| | 5-CV | $0.97 \pm 0.01$ | $0.88 \pm 0.04$ | $0.97 \pm 0.01$ | $0.97 \pm 0.01$ |
| | **Test** | **0.94** | **0.89** | **0.96** | **0.95** |

the advantage of looking at a larger context of the input and use information from the future to predict a given state, as far as this application is concerned, the improvement in the results is only marginal with respect to the seq2seq model.

## Broader Impact

Future large scale fusion devices such as ITER and DEMO are foreseen to operate in H-mode to optimize the energy confinement. An accurate model that can automatically detect these modes is an important component for optimizing plasma performance. Future studies remain to be done, such as the integration and commitment of the models in the Plasma Control System of existing fusion devices. However, the work done so far is an important progress and in what concerns the future societal consequences, we believe this work to bring us one step closer for the achievement of a sustainable, clean and abundant energy source that fusion technology aims to provide.

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# Appendix

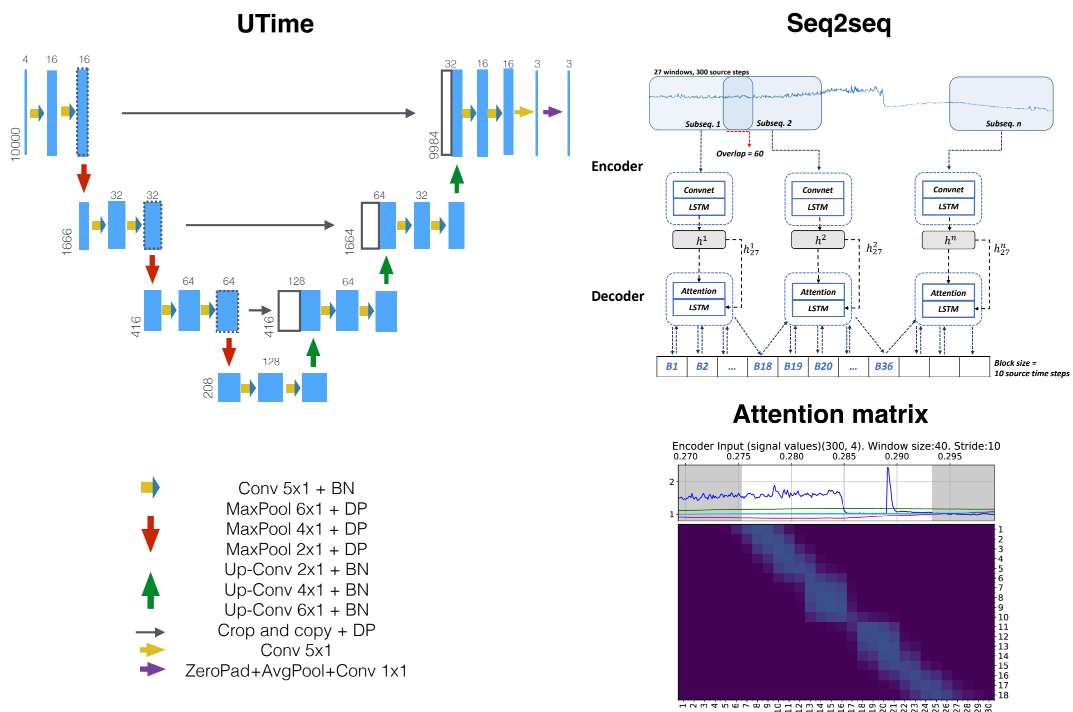


Figure 2: Network architectures details for UTime and sequence to sequence models. The 4 different channels shown as input in the UTime model correspond to the 4 sources used for training (PD, FIR, DML, IP) and the 3 channels in the output reflect the different plasma states targets.