Real-time Classification of L-H transition and ELM in KSTAR

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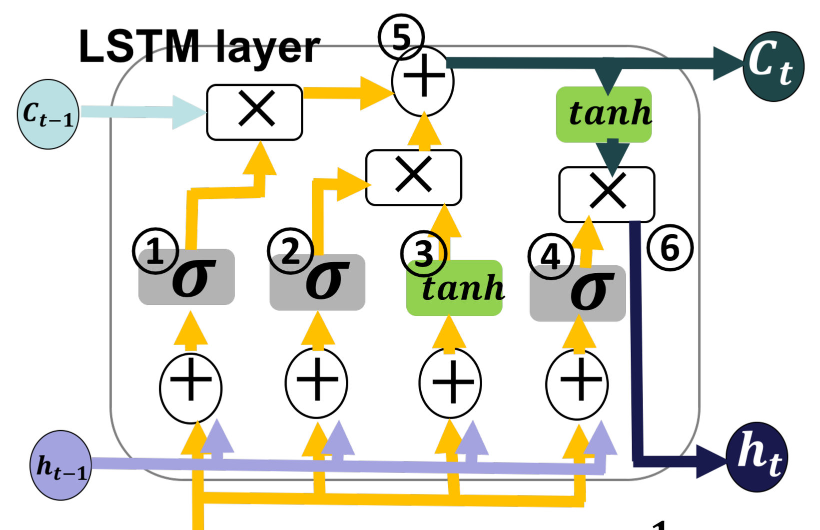
MOTIVATION

- It has been widely accepted that a **high confinement mode**(H-mode) operation is **necessary** for advanced tokamaks or ITER. However, when plasma is in H-mode, the **edge localized mode**(ELM) occurs at the plasma edge, which **release particles and energy** [1]. In case of ITER, a full tungsten divertor **cannot tolerate the heat load from the type-I ELM** [2]. Besides, in terms of plasma density feedback control, the fuel into the plasma **cannot be absorbed by gas puffing only due to the edge transport barrier** and the diagnostic values of the real-time plasma density are **abnormally observed by the ELM burst**.
- In order to help to control these problems, we need an **algorithm that can detect what the plasma mode is and make appropriate actuators activate**, such as gas puff, Supersonic Molecular Beam Injection (SMBI) [3], and so on, according to the detected plasma mode.
- From our previous study [4] on detection of the L-H transition in KSTAR, we showed the possibility of real-time detection with a SVM classifier trained through machine learning.
- To **overcome the previous results** and to apply **more suitable real-time algorithm** in KSTAR practically, we trained neural networks based on **long short-term memory** (LSTM) [5].

METHODS

- Feature selection
  - ➢ Selection criterion : indicate the occurrences of L-H transition and ELM phase
  - ➢ Selected two features to detect L-H transition and ELM in KSTAR [6-8]
    - ✓ **The first feature D_α** : special phenomenon that D_α signal is dropped when the transition occurs (poloidal D_α monitor #2 [9])
    - ✓ **The second feature $\overline{n_e}$** : rising gradient of $\overline{n_e}$ (line averaged electron density) signal (Millimeter Wave Interferometer (MMWI) [10] and Far-Infrared Interferometer (FIR)[11])
- Data preparation
  - ➢ The number of samples for training : **65 shots for training set** / 58 shots for test set in 2017 KSTAR campaign
    - ✓ down-sampled signals to **1KHz** for D_α and $\overline{n_e}$; 1 shot = 3000 data samples (3s)
  - ➢ rescaling : divided by 1/10 for D_α and $\overline{n_e}$
  - ➢ Data labeling (supervised learning) :
    - ✓ ***Label 1*** : L-mode, ***Label 2*** : Intermediate, ***Label 3*** : H-mode, and ***Label 4*** : ELM
- **Long Short-Term Memory** (LSTM) [5]
  - ➢ A novel kind of Recurrent Neural Network(RNN) **to solve vanishing gradient problem**
  - ➢ LSTM has key concepts which are cell state and three gates (forget, input, and output gates)
    - ✓ **Cell state** is a memory cell that store information
    - ➢ **Forget gate** can determine whether or not to reflect the previous information into the cell
    - ➢ Information at current time(or sequence) comes through **input gate**
    - ➢ **Output gate** generates new output(=hidden) state
- Network layer setting
  - ✓ Sequence input layer (input) => single LSTM layer (optimizer = ADAM [12]) => Fully connected layer

  => softmax layer => classification layer (output)



$(\sigma(x) = \frac{1}{1+e^{-x}})$

① **Forget gate**

$$f_t = \sigma(W_f X_t + R_f h_{t-1} + b_f)$$

② **Input gate**

$$i_t = \sigma(W_i X_t + R_i h_{t-1} + b_i)$$

③ **Cell candidate**

$$g_t = tanh(W_g X_t + R_g h_{t-1} + b_g)$$

④ **Output gate**

$$o_t = \sigma(W_o X_t + R_o h_{t-1} + b_o)$$

⑤ **Cell state**

$$c_t = f_t C_{t-1} + i_t g_t$$

⑥ **Output(hidden) state**

$$h_t = o_t tanh(c_t)$$

Network layer setting

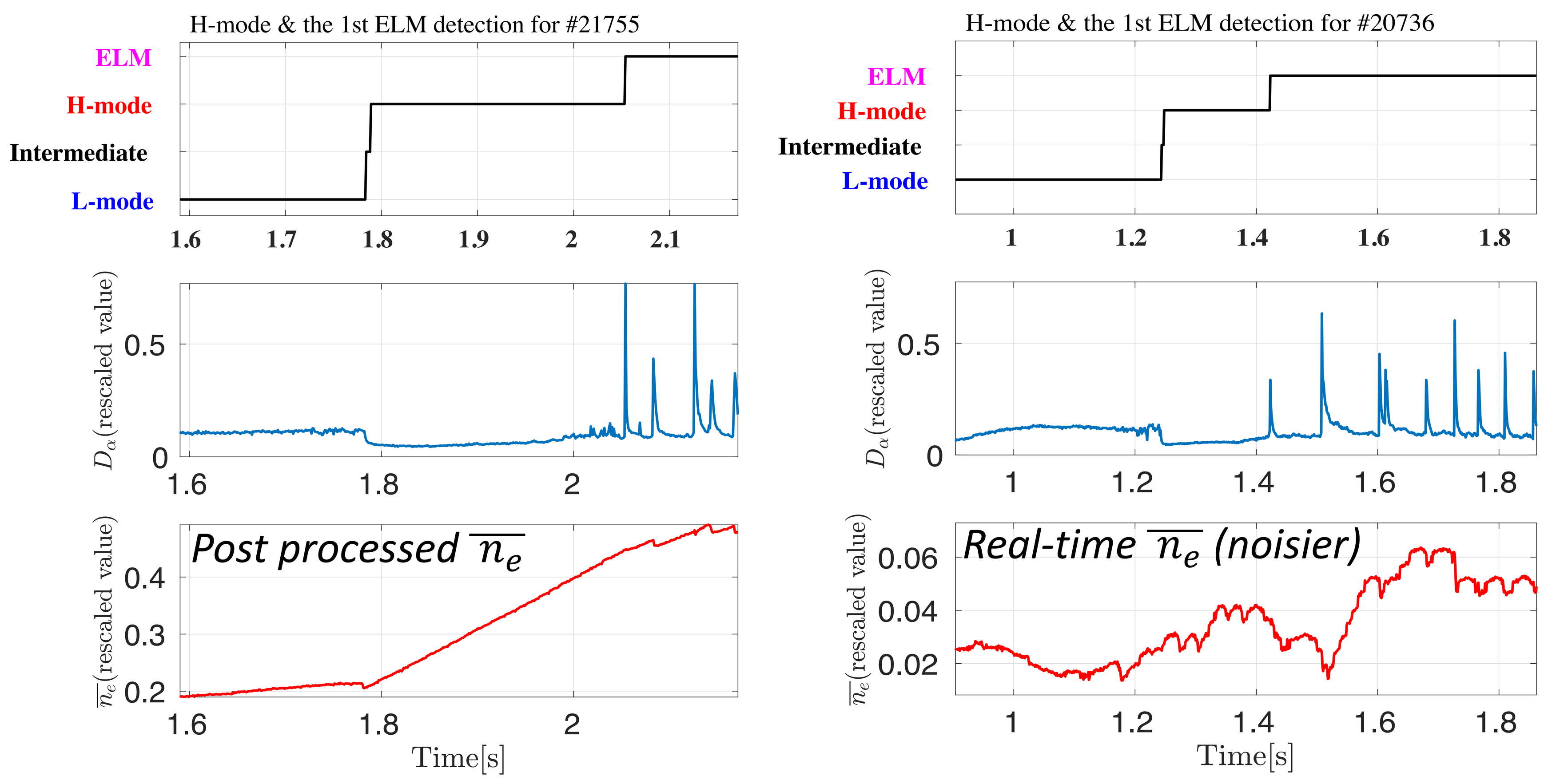
Layer	Setting
Sequence Input Layer	**Input : 2 (2 features) [2 x 1], length 3000**
LSTM Layer	**No. of hidden units : 300 [300 x 2]**
Fully Connected Layer	**No. of labels : 4 [4 x 300]**
Softmax Layer	**FC: [4 x 1] =>** $\frac{e^{(FC)}}{\sum e^{(FC)}}$
Classification Layer	$max(Softmax\ Layer)$ **=> Label 1 ~ 4; output**

RESULT

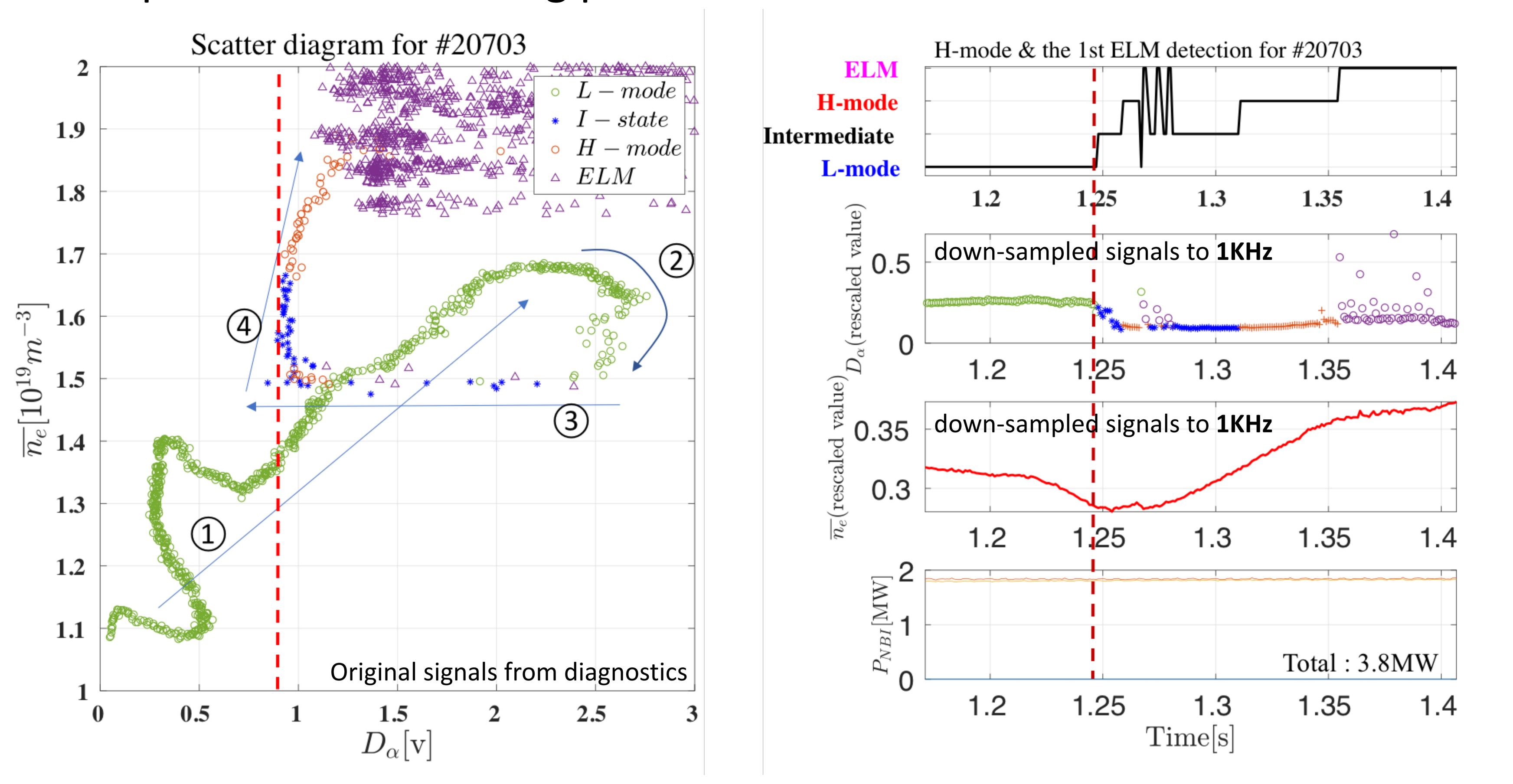
- In the previous study [4] using Support Vector Machine(SVM) [13], we obtained results about calculation time and accuracy for testset as follows.

	SVM classifier	LSTM classifier
Data set	2017 campaign data (139 shots)	2017 campaign data (123 shots)
Number of labels	2 (L- and H- mode)	4 (L-mode, intermediate state, H-mode, and ELM)
Calculation time per a sample	About 8 ms	About 250 μs
Classification average accuracy for test set (same shots in 2017campaign)	74.47% (58 shots)	94.45% (58 shots)

- In the 2018 KSTAR campaign, **434 shots** of the total 542 H-mode shots are successfully **classified**(**80.07%**)using D_α and post processed $\overline{n_e}$. **448 shots** of the total 533 shots are also successfully **classified(84.05%)** using D_α and real-time $\overline{n_e}$.
- This success rate includes the first ELM burst classification at least.



- Although classifier has never been trained to include ELM after L-H transition in the training step of the LSTM classifier, a result that is classified as ELM are shown after the L-H transition.
- The dithering phenomenon is sometimes associated with ELMs, so that data classified as ELMs during the occurrence of intermediate state can be evidence of dithering. This case shows a good agreement with the description of the dithering phenomenon.



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