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

Gi Wook Shin\textsuperscript{a}, J. -W. Juhn\textsuperscript{b}, G. I. Kwon\textsuperscript{b}, and S. H. Hahn\textsuperscript{a, b}

\textit{a.} University of Science and Technology (UST), Republic of Korea
\textit{b.} National Fusion Research Institute (NFRI), Daejeon, Republic of Korea
gwshin@nfri.re.kr

**MOTIVATION**

- It has been widely accepted that a \textit{high confinement mode} (H-mode) operation is necessary for advanced tokamaks or ITER. However, when plasma is in H-mode, the \textit{edge localized mode} (ELM) occurs at the plasma edge, which release particles and energy \cite{1}. In case of ITER, a full tungsten divertor cannot tolerate the heat load from the type-1 ELM \cite{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) \cite{3}, and so on, according to the detected plasma mode.
- From our previous study \cite{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) \cite{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 $D_{a}$: special phenomenon that $D_{a}$ signal is dropped when the transition occurs (poloidal $D_{a}$ monitor $\#2$) [9]
    - The second feature $\pi_{V}$: rising gradient of $\pi_{V}$ (line averaged electron density) signal (Millimeter Wave Interferometer (MMWI) [10] and Far-Infrared Interferometer (FIR)\cite{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 $D_{a}$ and $\pi_{V}$; 1 shot = 3000 data samples (3s)
  - rescaling: divided by 1/10 for $D_{a}$ and $\pi_{V}$
  - Data labeling (supervised learning):
    - \textbf{Label 1}: L-mode, \textbf{Label 2}: Intermediate, \textbf{Label 3}: H-mode, and \textbf{Label 4}: ELM
- Long Short-Term Memory (LSTM) \cite{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)
  - \textbf{Cell state} is a memory cell that store information
  - \textbf{Forget gate} can determine whether or not to reflect the previous information into the cell
  - Information at current time(or sequence) comes through \textbf{input gate}
  - \textbf{Output gate} generates new output(hidden) state
- Network layer setting
  - Sequence input layer (input) => single LSTM layer (optimizer = ADAM \cite{12}) => Fully connected layer => softmax layer => classification layer (output)

**RESULT**

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

<table>
<thead>
<tr>
<th>Data set</th>
<th>SVM classifier</th>
<th>LSTM classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>2017 campaign data</td>
<td>139 shots (139 shots)</td>
<td>123 shots (123 shots)</td>
</tr>
</tbody>
</table>
| Number of labels        | 2                     | (2, L- and H-mode)    | 4 | (L-mode, intermediate state, H-mode, and ELM)
| Calculation time per sample | About 8 ms           | About 250 μs          |
| Classification average accuracy for test set | (same shots in 2017 campaign) | 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 $D_{a}$ and post processed $\pi_{V}$. 448 shots of the total 533 shots are also successfully classified(84.05%) using $D_{a}$ and real-time $\pi_{V}$.
- 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.

**REFERENCES**