Contribution ID: **1250** Type: **Regular Poster**

Machine learning approach to understand the causality between solitary perturbation and edge confinement collapse in the KSTAR tokamak.

Tuesday 11 May 2021 14:00 (20 minutes)

Repetitive buildup and collapse of the edge confinement barrier (called pedestal) in H-mode plasmas can seriously damage the plasma-facing components in tokamak fusion devices [1]. Hence, an accurate understanding of the underlying mechanism of the collapse is essential for the safe operation of fusion devices. We have proposed the formation of a solitary perturbation (SP) in the edge as a candidate trigger of the pedestal collapse, based on our observation of SP within $\sim 100\ \mu$s before the onset of the collapse in the KSTAR [2]. Figure 1 shows an example of SP detected by a toroidal array of Mirnov coils (MCs). Low-pass filtering ($< 50\ k$Hz) of the MC signals reveals a temporally and spatially localized perturbation of high amplitude in proximity to the pedestal collapse, as highlighted in blue color in figure 1(d), which is not easily discernible in raw signals. The SP has distinct features in the spatial structure, rotational speed, and mode pitch, distinguished from the edge localized mode (ELM), which is widely known to cause the pedestal collapse.

Indico rendering error

```
Could not include image: [404] Error fetching image
```

However, a statistical study on extensive data would be a prerequisite before ascertaining the SP as the collapse trigger. We have constructed a machine learning (ML) model based on a convolutional deep neural network architecture to automate check on the concurrency of the pedestal collapse and the SP. The ML model takes sequential signals detected from 19 toroidal MCs as input and predicts whether each temporal frame corresponds to an SP. As it is required to identify the temporally shifted solitary patterns across the MCs, we adopted 2D convolution operations that capture local context patterns within the input matrix. We trained the network in a supervised manner on a training set consisting of signals with manually annotated SP locations and synthetic signals that imitate pedestal collapses without SPs. The inclusion of the synthetic data prevents the network from falsely recognizing the signals from the collapse as SPs due to their consistent co-occurrences.

The trained model achieves H_α of per-frame accuracy on the test set with the final score threshold of 5. The average precision (AP) of the model is about $30\ k$Hz. The AP measures the reliability of the per-frame prediction as a weighted mean of precisions in the precision-recall curve, where the precision and recall describe the ratio of correct SP predictions to all positive predictions and to all true SP cases, respectively. When applied to data sequences, our trained model achieves $\sim 90\ \mu$s of per-sequence accuracy for all the test data sequences. Here, the per-sequence accuracy measures the existence of SP based on the overall prediction of the model in a sequence. We further demonstrate the reliability of the model by visualizing the discriminative parts of the input signals that the model recognizes.

Indico rendering error

```
Could not include image: [404] Error fetching image
```

Finally, we performed a statistical analysis on the concurrence of pedestal collapse and SP using the developed model. The data set used for the analysis consists of a total of 16244 sequences, and each sequence is labeled with the existences of pedestal collapse and SP. For the collapse labeling criterion, we manually inspected the occurrences of the collapse in the sequences and found that all clear pedestal collapses have the maximum H-alpha intensity, $95.9\ \%$. For the SP labeling, we applied the ML model to the individual sequences and obtained the sequence prediction 0.7, which is the prediction score of the model accumulated the range of 0.88 centered on the midpoint of three consecutive positive predictions in a sequence. We chose $100\ \%$ as the criterion for the presence of SP based on our cross-validation with the training data set. Figure 2 plots the values of H_α and y_s to visualize the correlation between the two variables. We identify four regions, and a table in figure 2 presents the number of sequences in each region. Region 1 ascertains that the pedestal

collapse of high amplitude accompanies SP. Region 2 contains one minor exception, but it is not against the overall trend because the SP prediction score $H_{\alpha}^{max} > 1\times10^{21}$ is near the decision boundary. Region 3 and 4 represent the sequences without a clear signature of pedestal collapse. Most of these sequences have zero y_{s} and are located in Region 3. It is worth mentioning that many sequences in region 4 correspond to small pedestal collapse. Therefore, the most conservative interpretation of the statistical analysis is that a large pedestal collapse always coexists with SP.
Our results strongly support the SP as a pedestal collapse trigger. This conclusion suggests that studying the effect of SP on the collapse is essential to understand and control the edge pedestal collapse. Besides, our result is a meaningful example that illustrates the possibility of applying deep learning techniques for expedient analysis of complex MHD phenomena.

This work is supported by the Center for WISET grant funded by the MIST under the Program for Returners into R&D and NRF of Korea under grant no. NRF-2019M1A7A1A03088456.

References:
[1] A. Loarte et al, Plasma. Phys. Controlled Fusion 44, 1815 (2002)
[2] J. E. Lee et al, Sci. Rep. 7, 45075 (2017).

Affiliation

Pohang University of Science and Technology

Country or International Organization

Korea, Republic of

Author: LEE, Jieun (Pohang University of Science and Technology)

Co-authors: SEO, Hongsuck (Pohang University of Science and Technology); BAK, Jun Gyo (National Fusion Research Institute); YUN, Gunsu (Pohang University of Science and Technology)

Presenter: LEE, Jieun (Pohang University of Science and Technology)

Session Classification: P2 Posters 2

Track Classification: Magnetic Fusion Experiments