Autonomous detection and control of Sawtooth instability triggering ELM

Minseok Kim[1], SangKyeun Kim[2], Azarakhsh Jalalvand[1], Ricardo Shousha[2], Alvin Garcia[1,3], Max Curie[1], Jalal Butt[1] and Egemen Kolemen[1]

[1]Department of Mechanical & Aerospace Engineering, Princeton University
[2]Princeton Plasma Physics Laboratory, Princeton, NJ, US
[3]Oak Ridge Institute for Science and Education, Oak Ridge, TN 37830, USA

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E-mail: mseokim@princeton.edu

Introduction

1. A single burst of edge localized mode (ELM) can severely damage the plasma facing components (PFC) of ITER or any other high-performance future tokamaks.
2. Hence, we have developed adaptive ELM controller [1-4] using resonant magnetic perturbation (RMP) to suppress/mitigate ELMs while optimizing the performance of KSTAR and DIII-D devices.
3. For further optimization of performance, we need to distinguish if ELM is originated from Sawtooth or not as Sawtooth induced ELM can not be suppressed/mitigated.

Focus of the poster

1. Methodology of labeling ELMs induced by Sawtooth at DIII-D tokamak
2. Principal component analysis (PCA) to decrease the dimensionality
3. Classification of ELMs using random forest classifier

1. Labelling ELMs originated by Sawtooth

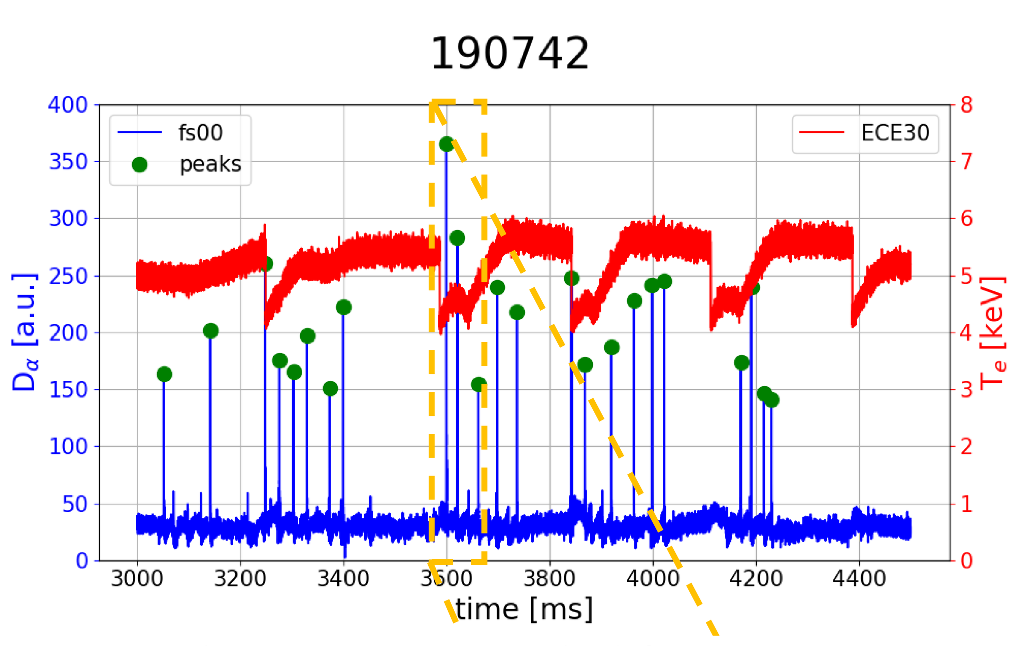


Fig.1. Core ECE and edge D-α signals @DIII-D #190742

- Core Electron Cyclotron Emission (ECE) signals show Sawtooth oscillations and peaks in the D-α signals show ELM bursts
- If there's sudden drop of core ECE signals prior to the ELM peak within 15ms, we label the peak to be originated by Sawtooth
- Peaks in the filter scope signals are found by *scipy.signal.find_peaks()* [5]

$\frac{dD-\alpha}{dt}$ @ $t_0 - 15ms$
⋮
$\frac{dD-\alpha}{dt}$ @ t_0
$\frac{dECE}{dt}$ @ $t_0 - 15ms$
⋮
$\frac{dECE}{dt}$ @ t_0

< Feature vector >

$t \in \{0, 1, 2\}$

< Label >

\# of features : 1,500
\# of datasets : 74,252

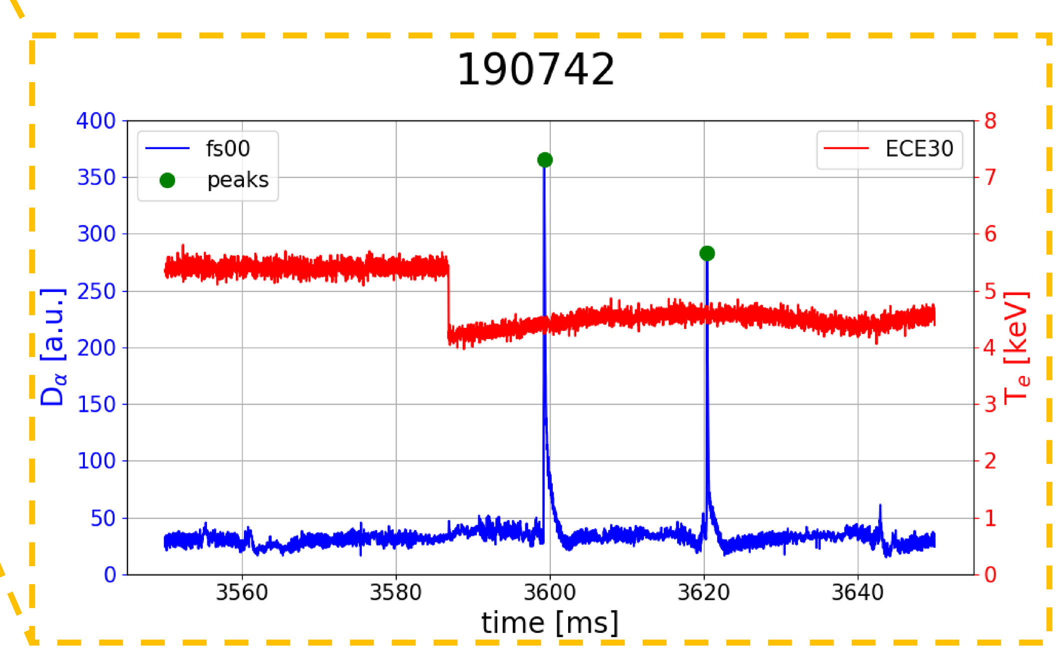
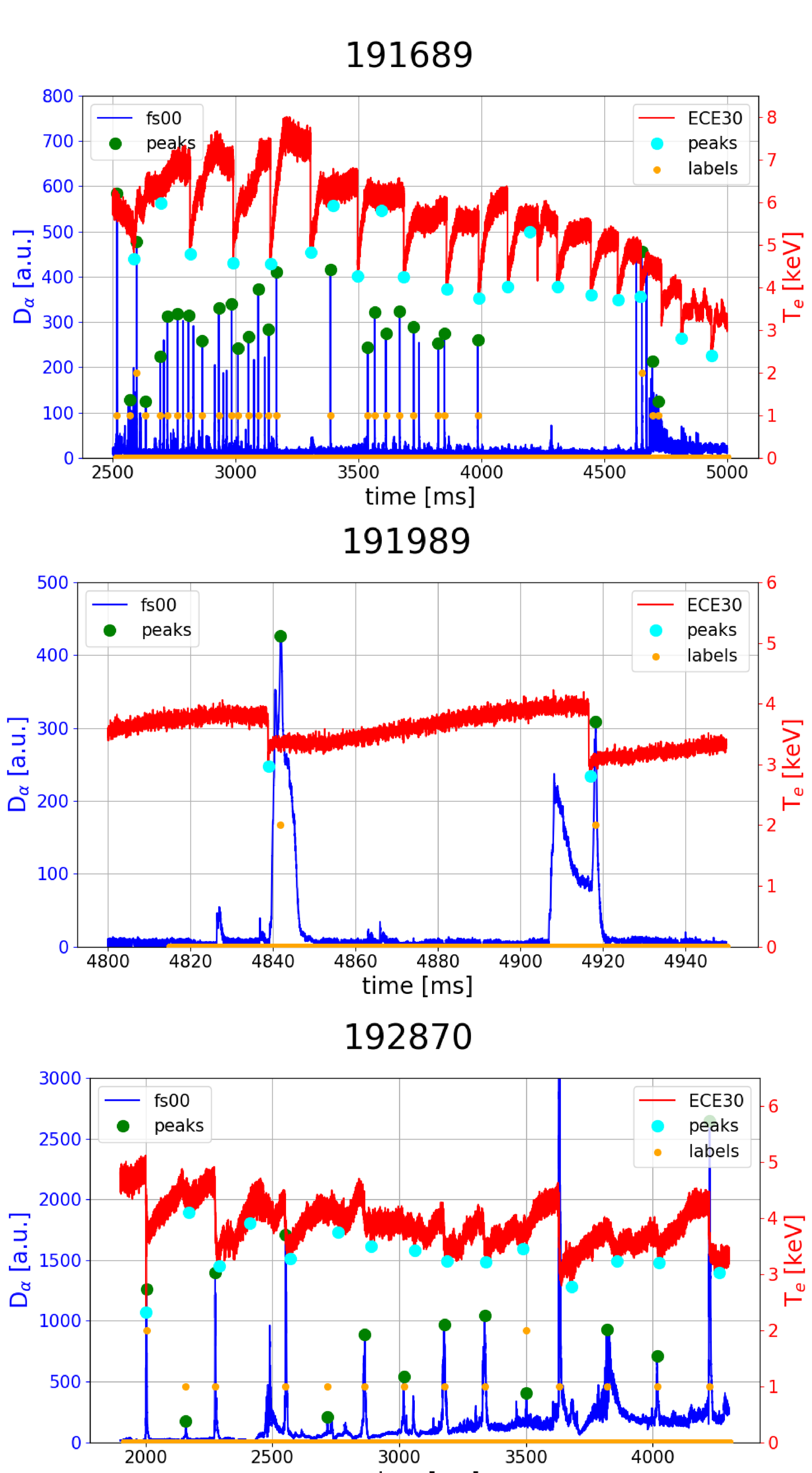
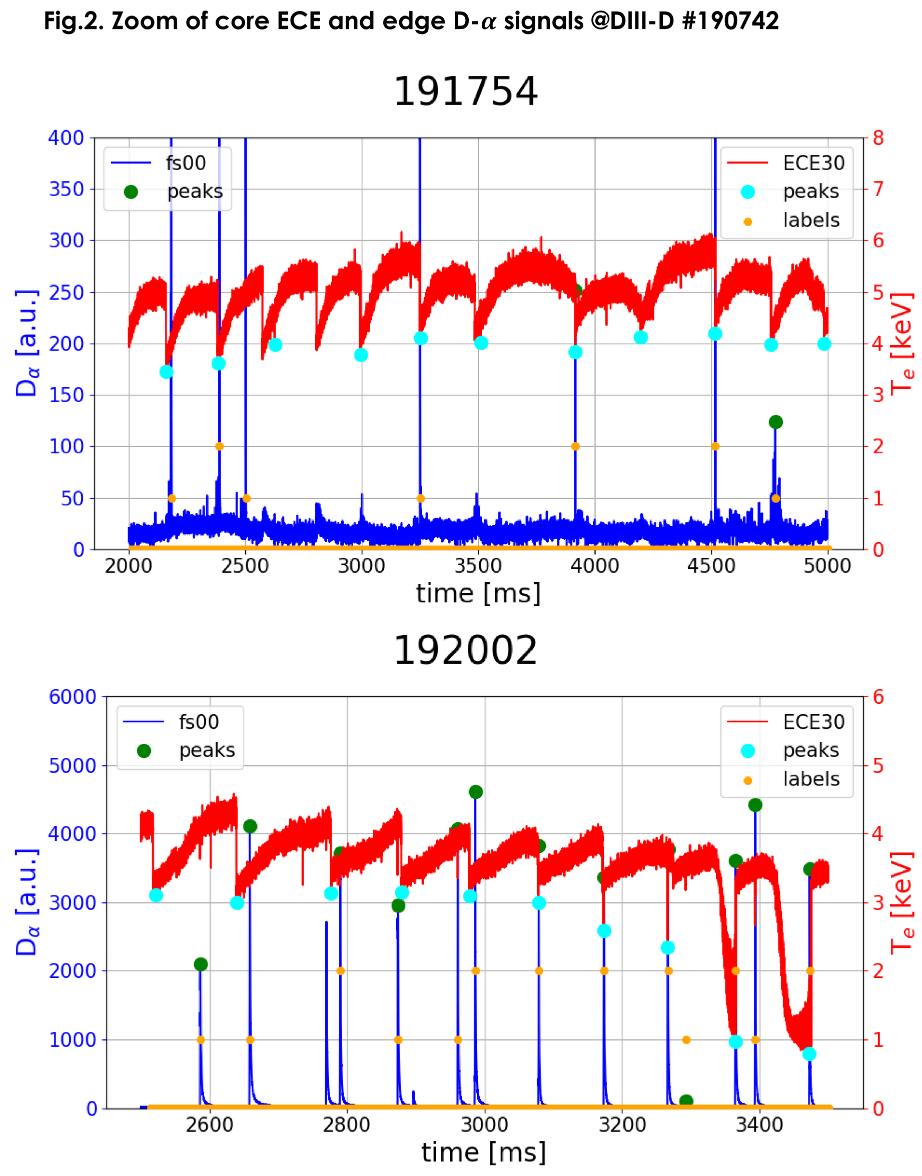


Fig.2. Zoom of core ECE and edge D-α signals @DIII-D #190742





- Six shots are collected to train and test the model. (190742 , 191689, 191754 , 191989, 192002, 192870)

	Label 0	Label 1	Label 2
#	523,012	70	17

Fig.3. Datasets

2. Principal component analysis

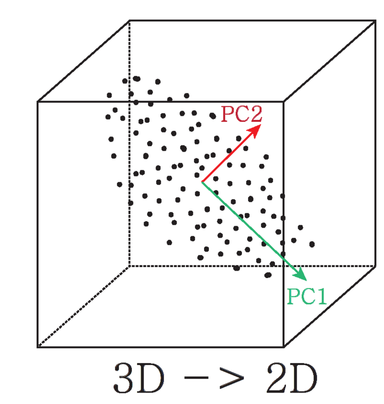


Fig.4. Example of dimensionality reduction

PCA : Principal Component Analysis [6]

1. Principal components explain most of the variances.
2. By projecting the data on the PCs, we can reduce the dimension.

- Principal component analysis (PCA) is applied to decrease the dimensionality of dataset.
- 562 principal components can explain 99% of dataset's variance.
- The feature vectors are projected on the 562 -dimensional space.

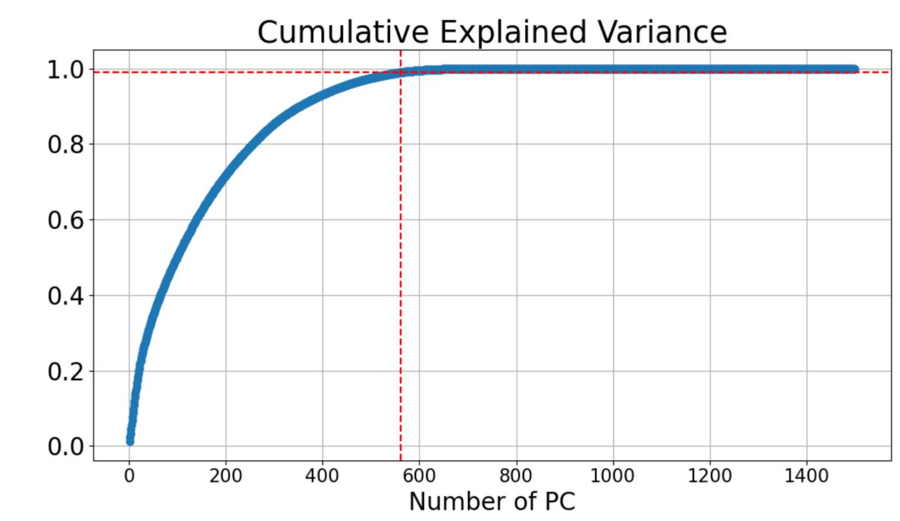


Fig.5. Cumulative explained variance of the dataset

3. Random forest classifier

- Random forest classifier performs well even for the small dataset.
- The class 0 is under sampled to have same number with the class 1.
- Train and test sets are split with the ratio of 9:1.
- Cross validation with 5 folds is applied for the hyper-parameter optimization.
- Weighted F1-score is set as the figure-of-merit.
- Class weights are decided by the train dataset.
- Datasets are normalized to have zero mean and unit variance.

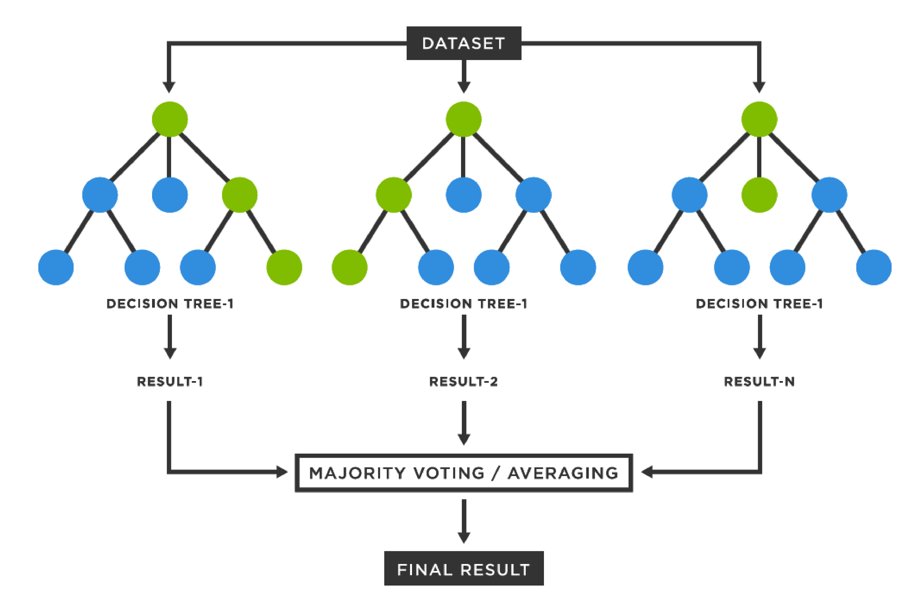


Fig.6. Illustration of random forest classifier [7]

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Weighted F1-score	0.90	0.89	0.96	0.82	0.82

Fig.7. Weighted F1-scores of five folds

Max depth	Min samples leaf	Min samples split	# of estimators
None	8	20	200

Fig.8. Best model

		Prediction		
		Class 0	Class 1	Class 2
Real	Class 0	6	1	0
	Class 1	0	7	0
	Class 2	0	1	1

Fig.9. Confusion matrix for the test dataset

	Precision	Recall	F1-score
Class 0	1.00	0.86	**0.92**
Class 1	0.78	1.00	**0.88**
Class 2	1.00	0.50	**0.67**

Fig.10. Figure of merits for the test dataset

4. Conclusions and Future works

Conclusions

- I could label the D-alpha peaks originated by Sawtooth using ECE30 and filterscope00.
- Classification has done using random forest classifier on the DIII-D datasets.
- We could verify possibility of real-time detection of D-alpha peaks originated by Sawtooth.

Future works

- Making larger dataset by looking into more recent shots. (Especially this year's)
- Verifying that 15ms time window is appropriate to decide if D-alpha peak is come from Sawtooth.
- Applying advanced models for the larger datasets.

Acknowledgements

1. Evans, T. E., et al. (2006). "Edge stability and transport control with resonant magnetic perturbations in collisionless tokamak plasmas." nature physics 2(6): 419-423.
2. Shousha, R., et al. (2022). "Design and experimental demonstration of feedback adaptive RMP ELM controller toward complete long pulse ELM suppression on KSTAR." Physics of Plasmas 29(3): 032514.
3. Kim, S., et al. (2022). "Nonlinear MHD modeling of n= 1 RMP-induced pedestal transport and mode coupling effects on ELM suppression in KSTAR." Nuclear Fusion 62(10): 106021.
4. Kim, S., et al. (2022). "Optimization of 3D controlled ELM-free state with recovered global confinement for KSTAR with n= 1 resonant magnetic field perturbation." Nuclear Fusion 62(2): 026043.
5. https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.find_peaks.html
6. Aurélien Géron.『Hands-On Machine Learning with Scikit-Learn and TensorFlow Concepts, Tools, and Techniques to Build Intelligent Systems』.O'Reilly Media(2017)
7. https://medium.com/@denizgunay/random-forest-af5bde5d7e1e

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