ID: 549

Disruption Predictor Based on Neural Network and Anomaly Detection

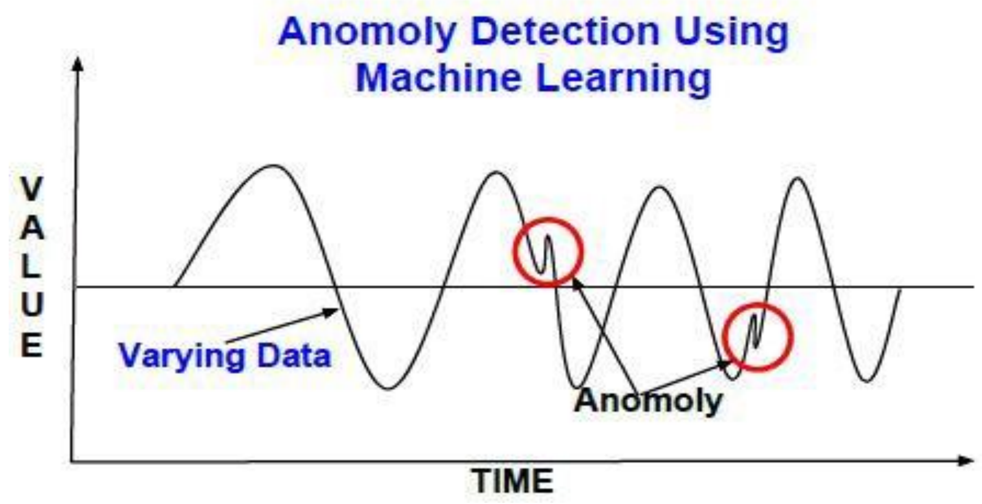
Wei Zheng, Qiqi Wu, Ming Zhang, and J-TEXT team
zhengwei@hust.edu.cn
International Joint Research Laboratory of Magnetic Confinement Fusion and Plasma Physics, Huazhong University of Science and Technology

Introduction

- ➢Tokamaks will have disruptions. Disruption will do harm to large tokamaks.
- ➢Inevitable disruptions should be mitigated by disruption mitigation system (DMS). Disruption prediction will be in charge of triggering the DMS.
- ➢Physics based disruption prediction is not very reliable.
- ➢Machine learning (ML) based disruption prediction needs disruptive shots and is a black box thus can not extrapolates to other devices
- ➢Future large tokamaks will not be able to provide disruption samples to develop a ML based predictor.

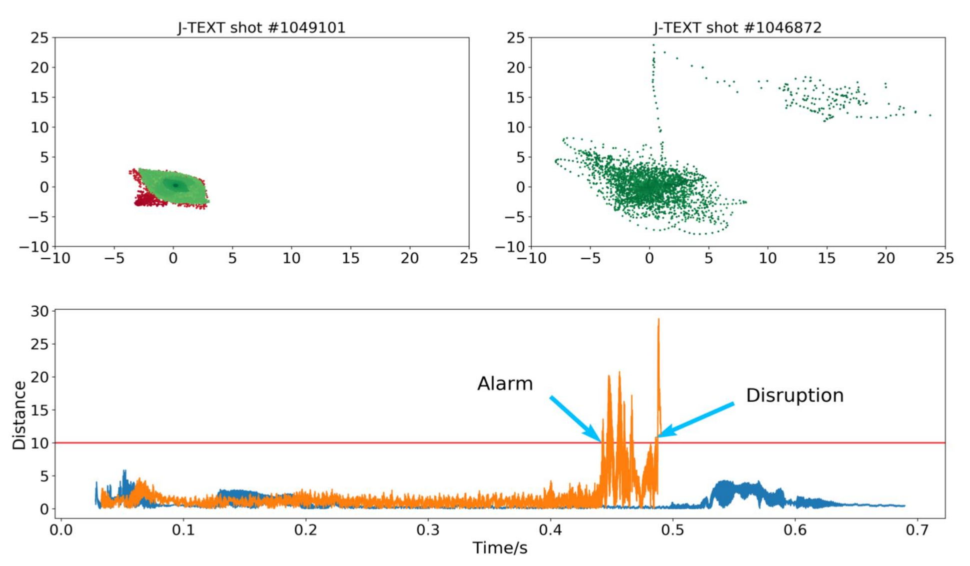
Anomaly detection

- ➢Anomaly detection is the identification of rare events which raise suspicions by differing significantly from the majority of the data.



- ➢Applicable Use Cases:
  - ➢Very unbalanced training dataset — Disruptions are far less then non-disruptive shots
  - ➢Positive samples are rare and expensive — Disruptions are harm and must be avoid for large tokamaks
  - ➢Characteristics of the positive sample are unknown — Physics of disruption is not clear
  - ➢Thus good fit for disruption prediction

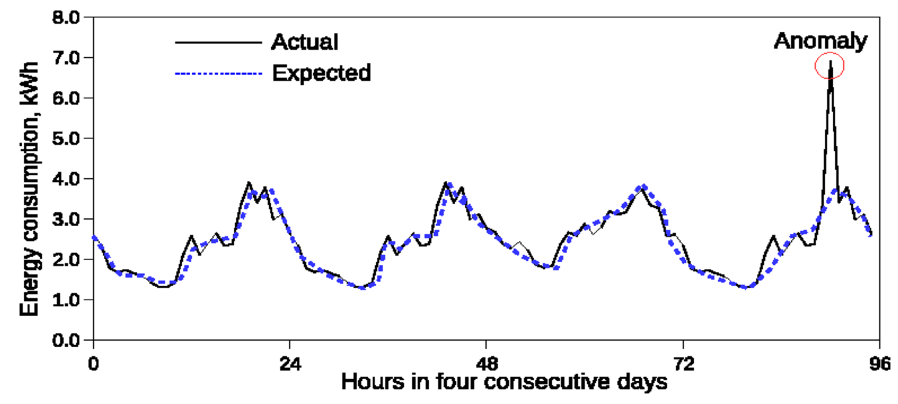
Preliminary experiment on J-TEXT



- ➢Based on Single signal predictor based on anomaly detection (SPAD) developed by JET
- ➢Adopted, modified and tested using J-TEXT signal
- ➢Using rule based feature extraction: Haar wavelet
- ➢Result: High success rate (TPR), but very low warming time (Twarn), and very high false alarm rate (FPR

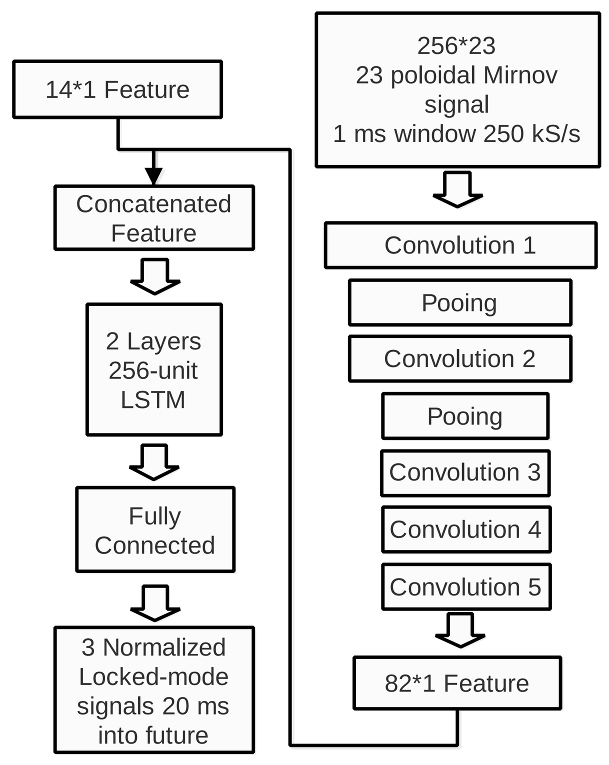
Deep Learning Anomaly Detection

- ➢One time series anomaly diction technique:
- ➢Using a regression model to predict the future value of some given signal,
- ➢it the actual signal deviate from the expected value than an anomaly if found



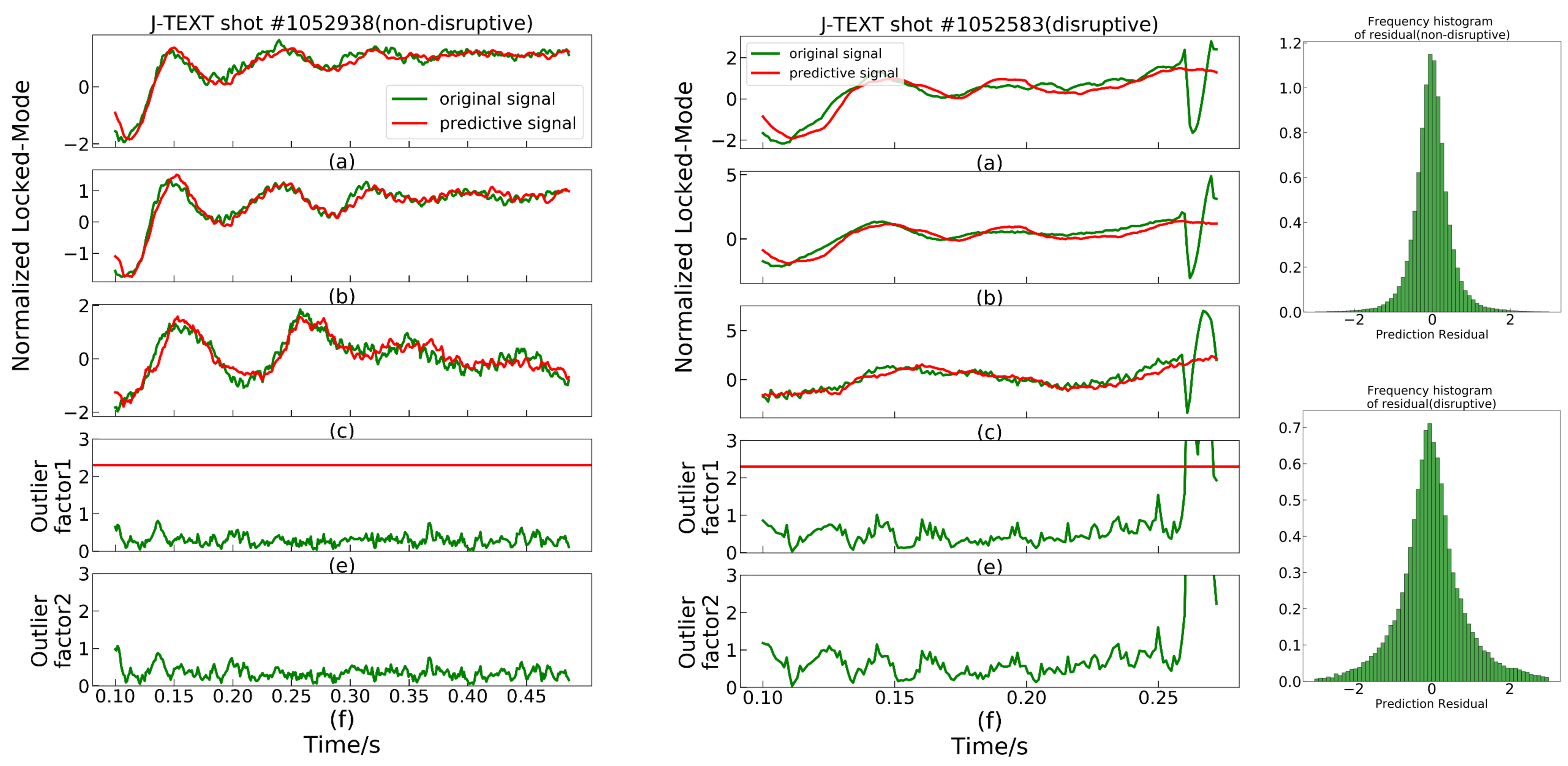
Regression based Anomaly Detection

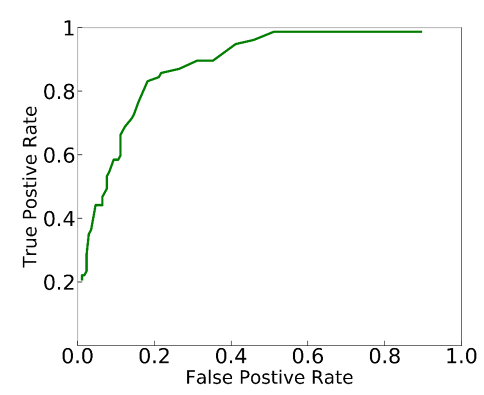
- ➢ **Time series Deep learning prediction model**



Exsad*6
IP
Bt
AXUV
Soft X-ray
C_{III}
ECE
Ivfp
Ihfp
Mirnov*23

Data set	Shot Number
Training	320 Non-disruptive only
Validation	80 Non-disruptive only
Test	170 Non-disruptive + 77 disruptions





Threshold=2.3	
True Positive:	0.83
False Positive:	0.18
Average Warning Time	36 ms

Summary and Future work

- ➢Summary:
- ➢Possible to build a ML disruption predictor without any disruptions for training
- ➢An anomaly detection and neural network based predictor is developed and tested using J-TEXT data, But, the performance of the predictor is not as good as supervised ML disruption predictor.
- ➢But there is room for improvement.
- ➢Future Work:
- ➢More work on signal selection, development on the disruption database and get cleaner data, hyper-parameter search and Adaptive training strategies.

Contact Us: zhengwei@hust.edu.cn, wuqiqi@hust.edu.cn

Address: School of Electrical and Electronic Engineering, Luoyu Rd. #1032, Huazhong University of Science and Technology, Wuhan 430074, China