MULTI-DIAGNOSTIC CLASSIFICATION OF ALFVÉN EIGENMODES USING MULTIMODAL MACHINE LEARNING

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Introduction

Alfvén Eigenmodes (AEs)
- AEs are driven by energetic particles that drive shear Alfvén waves in magnetically confined plasmas
- AE modes are important as they will eject high energy particles out of the plasma, reducing confinement and possibly damaging chamber walls

How We Find AEs
- Since AEs cause magnetic field fluctuations, we can find them in the spectra of many diagnostics such as:
  - Electron Cyclotron Emission (ECE)
  - CO2 Interferometry
  - J0 signals (MPI)
  - Beam Emission Spectroscopy (BES)
- After a shot, we can analyze spectrograms of the signals to see where AEs were present (see Fig. 1)

Goals of Study
- Real-time detection of AEs cannot be achieved by regular classifiers
- Answer the questions:
  - What diagnostics are best for real-time AE classification?
  - How robust will these detectors be to noise and detector dropouts?

Previous Works and their Drawbacks
- ECE based Reservoir Computing Network classifier [1]
  - Uses raw ECE data and can run in real-time
  - Limited to single diagnostic
- ECE based classifier using spectrograms [2]
  - Achieves better performance and finds locations of AEs
  - Processing of spectrograms is not feasible in real-time and model is limited to only ECE

Diagnostics

EVALUATING MODELS

Model Architecture

- Early Fusion
- Late Fusion

Model Predictions

Figure 1: Spectrograms showing (a) ECE, (b) CO2, and (c) MPI raw signals (upper plot) and filtered spectra (lower plot). A combination of RISA and TAE activity can be seen in the green boxes.

Figure 2: Model predictions for testing shots 142111 and 170660 in the left and right columns, respectively. Vertically: we have 5 AEs. In each plot, we have the true label (green dashed line), model prediction (solid blue line), and the threshold value (orange dashed line). When the prediction is above the threshold, our model is saying an AE is present.

Signal Noise
- ECE has the problem of cutoff—at certain resonant frequencies, no ECE can be seen
- CO2 can have linear drifts throughout a shot
- These drifts can have a range of slopes

Evaluating Models

<table>
<thead>
<tr>
<th>Model</th>
<th>ECE</th>
<th>CO2</th>
<th>TAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early Fusion</td>
<td>63.2%</td>
<td>63.5%</td>
<td>65.7%</td>
</tr>
<tr>
<td>ECE Only</td>
<td>41.7%</td>
<td>53.5%</td>
<td>51.1%</td>
</tr>
<tr>
<td>CO2 Only</td>
<td>23.1%</td>
<td>40.7%</td>
<td>51.4%</td>
</tr>
<tr>
<td>MPI Only</td>
<td>14.8%</td>
<td>40.7%</td>
<td>58.1%</td>
</tr>
<tr>
<td>Late Fusion</td>
<td>38.9%</td>
<td>51.7%</td>
<td>61.2%</td>
</tr>
<tr>
<td>ECE + CO2 TF</td>
<td>61.5%</td>
<td>62.5%</td>
<td>63.9%</td>
</tr>
<tr>
<td>ECE + MPI TF</td>
<td>57.7%</td>
<td>64.1%</td>
<td>61.8%</td>
</tr>
<tr>
<td>CO2 + MPI TF</td>
<td>28.2%</td>
<td>54.7%</td>
<td>65.6%</td>
</tr>
</tbody>
</table>

Table: Values in table are the TPRs with a threshold decided by an FPR = 10% in the validation data.

Since our dataset is skewed towards predominantly no AEs, we would find our model would perform “better” by always giving 0% AE probability. We use the TPR and FPR metrics to account for this uneven distribution of training data.

TF stand for Tensor Fusion—a input preprocessing that takes the outer product of the two signals to get the full cross-correlation matrix.

Discussion

Conclusions
- Magnetics (MPI) are extremely important
- ECE provides strong benefit while CO2 is much less helpful in early fusion models
- Late fusion provides classification equal to early fusion, although more sensitive to signals as a whole

Future Possibilities
- Turn detector model into predictor. With a predictor, we can train a reinforcement learning based controller to adapt and avoid AEs during shots
- Explore spectrogram-based models that could use FPGAs to be run in real-time

Sensitivity Analysis

Figure 3: We compare the model’s TPR as diagnostics dropout—all channels set to 0. The x-axis tells us which diagnostic has had all inputs set to 0. The threshold is adjusted so that each has an FPR = 10% on the validation data. (a) The early fusion model. We have the TPRs for the full input on the right and we see how it changes when we set ECE, CO2, or MPI to 0. (b) Late fusion model with the same input modifications.

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References