Early Detection of Combustion Instability by Neural-Symbolic Analysis of Hi-speed Video

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Problem

Combustion instability reduces **efficiency** and **longevity** of gas-turbine engines

- Significant **anomaly** characterized by high-amplitude **flame oscillations** at discrete frequencies
- Arises from positive coupling between heat release rate oscillations and the pressure oscillations
- Shows multi-scale **coherent structures** (fluid-mechanical structures) associated with coherent phase of high vorticity, causing high velocity oscillations

Objective: Early detection of combustion instability from hi-speed video via capturing spatiotemporal evolution of coherent structures

Experimental Setup

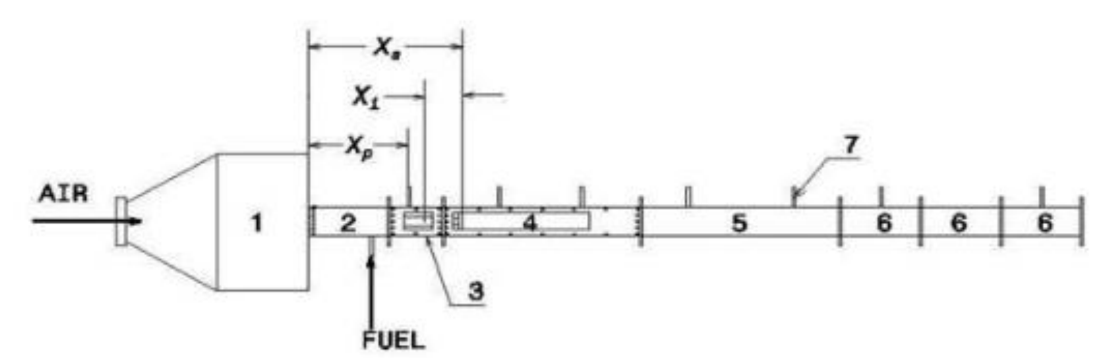

Fig 1: Schematics of experimental apparatus. 1 – Settling chamber, 2 – inlet duct, 3- inlet optical access module, 4-test section, 5&6 – big and small extension ducts, 7- pressure transducers, Xs – swirler location, Xp – transducer port location, Xi – fuel injection location

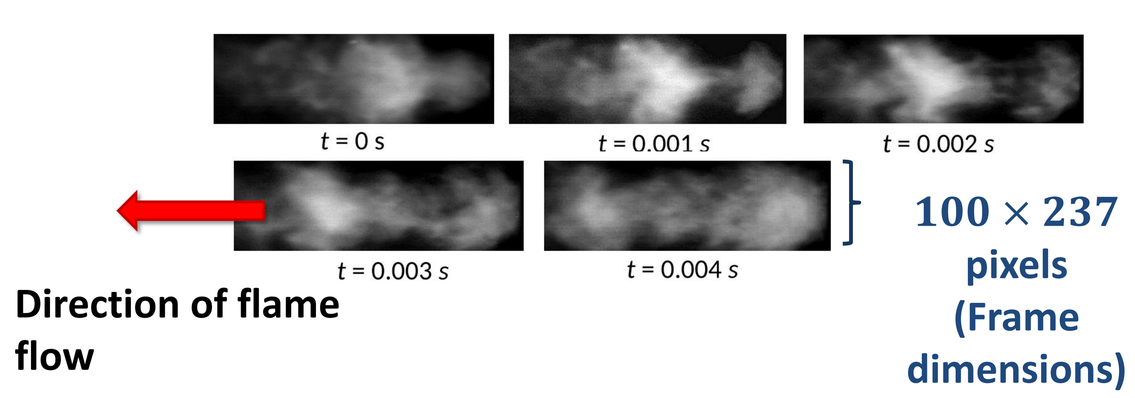

Fig 2: Sequence of Unstable Flame Images

- For testing, **4 instability conditions** were induced with different air flow rate (AFR), fuel flow rate(FFR), premixing levels. 3 seconds of hi-speed videos recorded @ 3000 fps **(9000 frames/condition)** for each condition.
- While testing, the proposed framework is applied on 7 seconds video (@3000 fps) where combustion attains instability from stability via intermittency for various transition conditions. Each called **'transition data'.**

Neural-Symbolic Approach

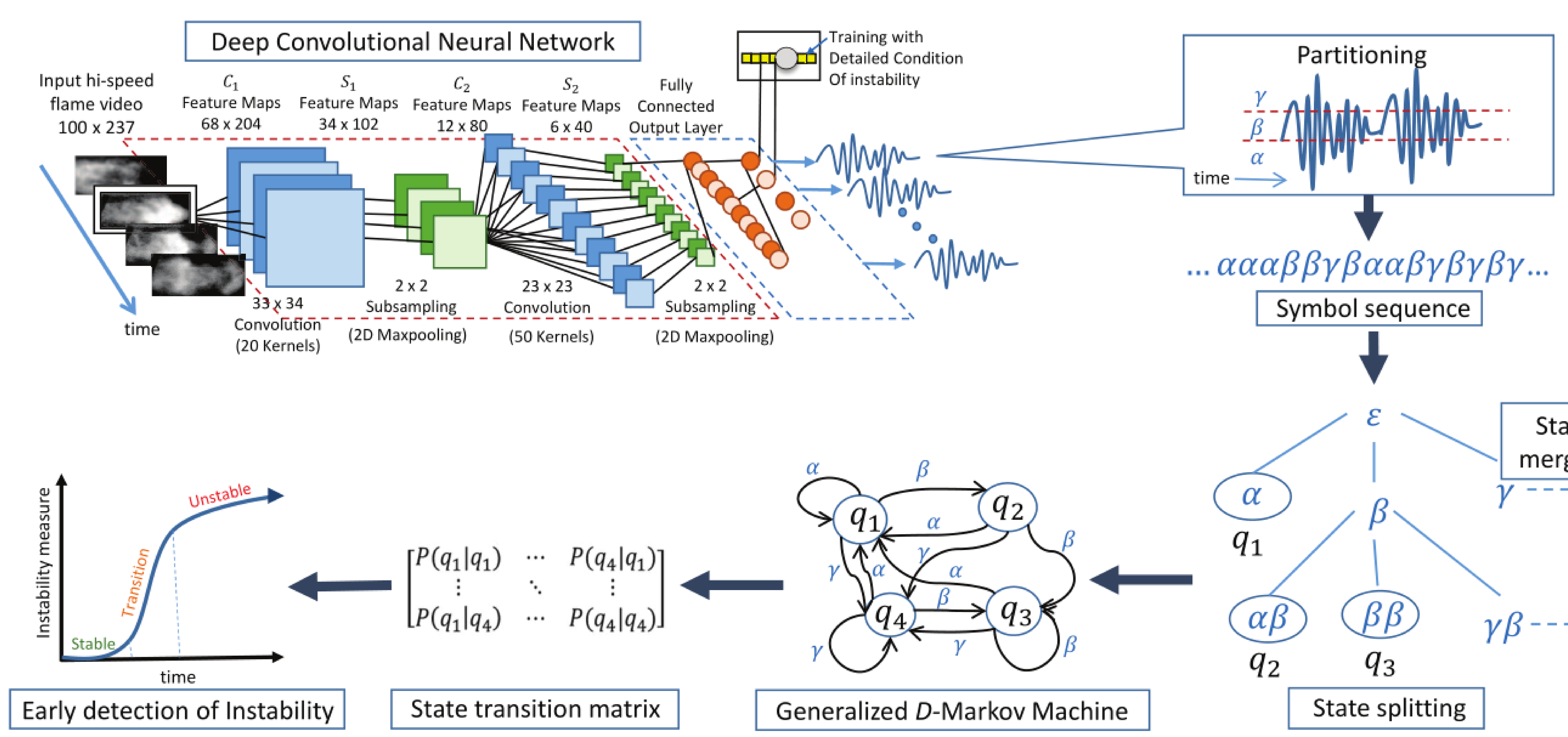

Fig 3: Neural-symbolic Dynamics Architecture

- Use deep **Convolutional Neural Network (CNN)** in the **lower layer** as a **feature extractor** to learn meaningful patterns from unstable flame images that can be argued as coherent structures.
- Use **symbolic approach** (i.e., Symbolic time series analysis, STSA) at the **upper layer** to capture temporal dynamics of the sigmoid outputs from fully connected layer. **Generalized D-Markov machine[eqn. 1] is constructed** by state splitting (via minimizing entropy rate [eqn. 3]) and state-merging (merging [eqn. 4] neighborhood states [eqn. 5] in probabilistic finite state machine space).
- **Train and validate model** on different operating conditions (air flow rate, fuel flow rate, air-fuel premixing level)

$$P[S_n|\dots s_{n-D}\dots s_{n-1}] = P[s_n|\, s_{n-D}\dots s_{n-1}] \quad (1)$$

D-Markov Machine

$$\hat{\pi}(q,\sigma) = \frac{1+N(q\sigma)}{|\Sigma| + N(q)} \forall \sigma \in \Sigma \forall q \in Q; P(q) = \frac{1+N(q)}{|Q| + \sum_{q' \in Q} N(q')} \forall q \in Q \quad (2)$$

Estimated Morph Matrix and Stationary State Probability Vector

$$H(\Sigma|Q) \triangleq \sum_{q\in Q} P(q)H(\Sigma|q) = -\sum_{q\in Q}\sum_{\sigma\in\Sigma} P(q)P(\sigma|q)\log P(\sigma|q) \simeq -\sum_{q\in Q}\sum_{\sigma\in\Sigma}\hat{P}(q)\hat{\pi}(q,\sigma)\log\hat{\pi}(q,\sigma) \quad (3)$$

D-Markov Entropy Rate

$$\Psi(K_1,K_2) \triangleq \lim_{n\to\infty}\sum_{j=1}^{n}\frac{\left\|P_1(\Sigma^j) - P_2(\Sigma^j)\right\|_{\ell_1}}{2^{j+1}} \quad (4)$$

State Merging

$$\mathcal{M}(q,q') \triangleq \|\hat{\pi}(q,\cdot) - \hat{\pi}(q',\cdot)\|_{\ell_1} = \sum_{\sigma\in\Sigma}|\hat{\pi}(q,\sigma) - \hat{\pi}(q',\sigma)| \quad (5)$$

Distance Function

Results and Discussions

Training deep CNN

- Trained with only unstable combustion conditions (24,000 training examples, 12,000 validation data)
- **CNN architecture**: 2 (convolutional + pooling) layers, followed by 100 and 10 fully connected hidden layer for dimension reduction and extraction of sigmoid activations

STSA-based Instability Measure

- Each sigmoid activation unit (out of 10) **generates a time series** for one transition dataset.
- Time window **output of activation unit is symbolized** by Maximum Entropy Partitioning (MEP).
- **State probability vector [eqn. 2] arises** from D-Markov machine at each time window is the feature capturing the extent of flame instability.
- Instability measure is the **L2-norm distance** from reference stable state vector.

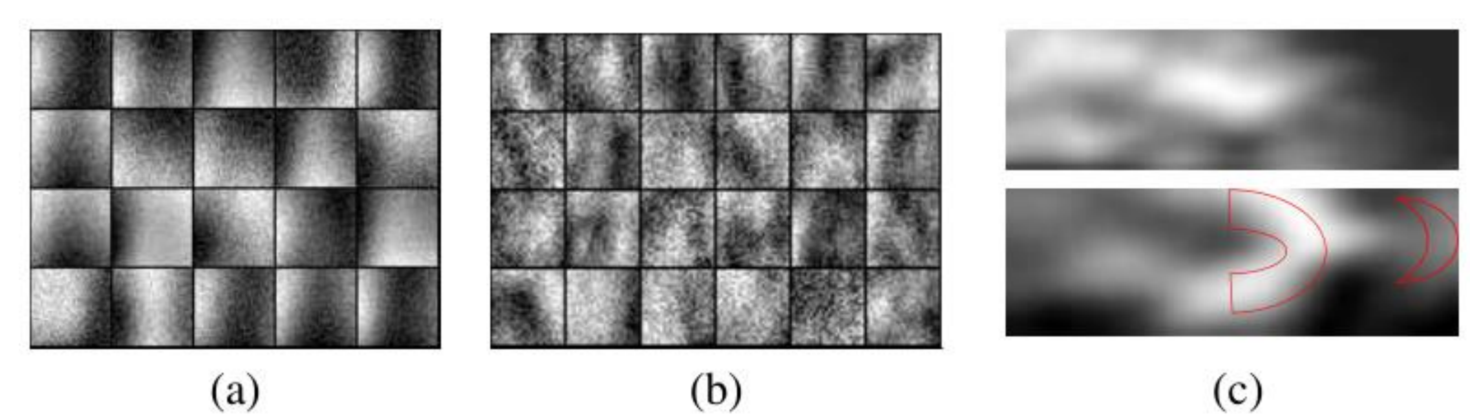

Fig 4: Filter visualization at convolutional layer (a) one and (b) two. (b) shows fragmented **representations of coherent structures** that are visible in unstable flame. (c) **Feature maps** of a stable frame (top) and an unstable frame (bottom) after applying first convolutional layer filter. Red outline on the unstable flame visualization shows the **mushroom-shaped coherent structure**

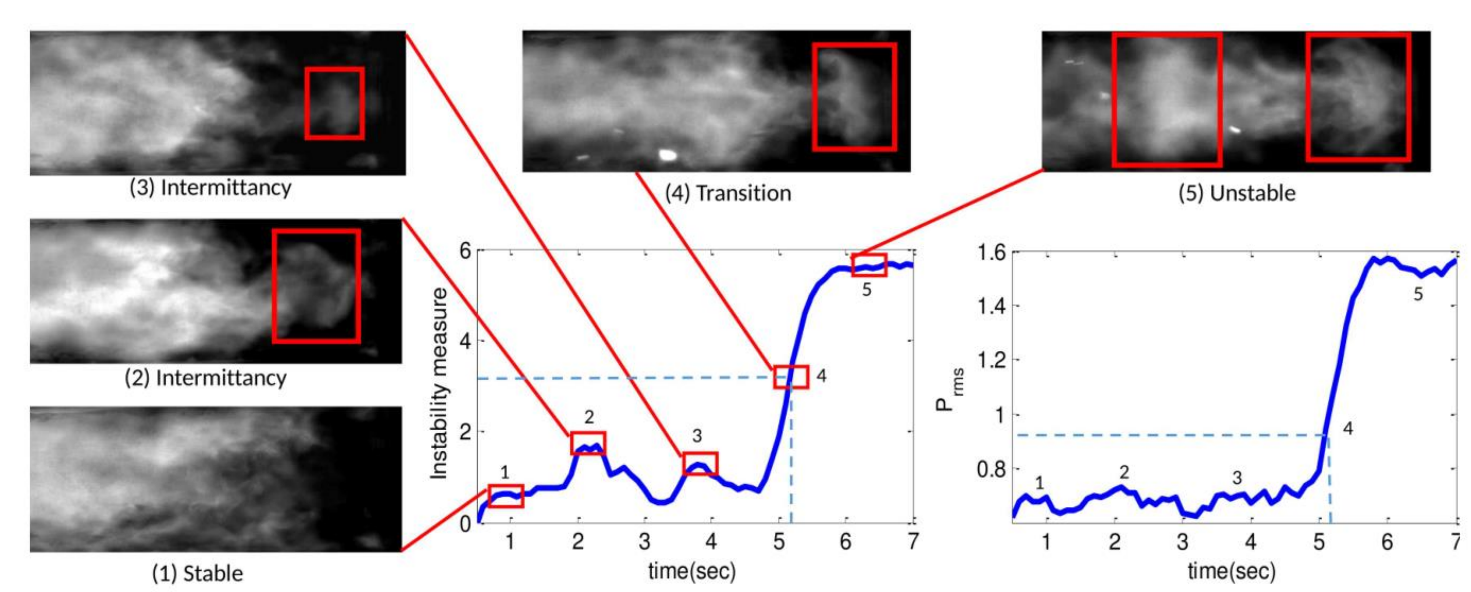

Fig 5: (Left) Variation of the proposed instability measure with time. Regions denote different combustion states (stable, temporary intermittancy, and unstable). Coherent structures detected by CNN+STSA are highlighted with the red box. **(Right)** rms variation of the pressure to provide a rough idea on ground truth. Progression of P_{rms} cannot detect the aforementioned precursors.

Comparing "CNN+STSA" with "PCA+STSA"

- Transition jump of instability measure from stability to instability for CNN+STSA is larger than PCA+STSA.
- CNN+STSA can detect intermittency precursor unlike PCA+STSA.

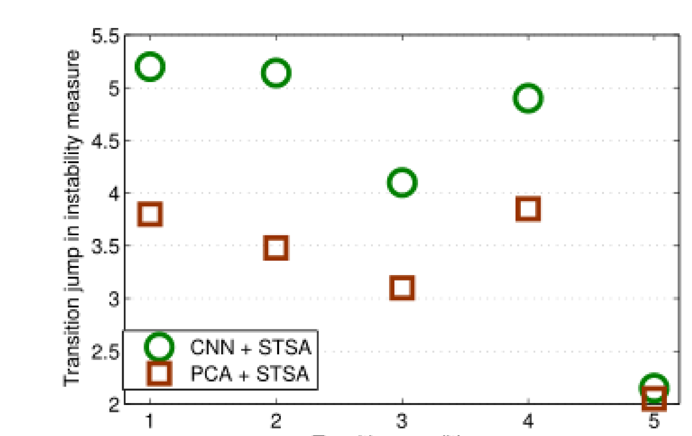

Fig 6: Comparison of sudden change in instability measure for 4 different transition conditions

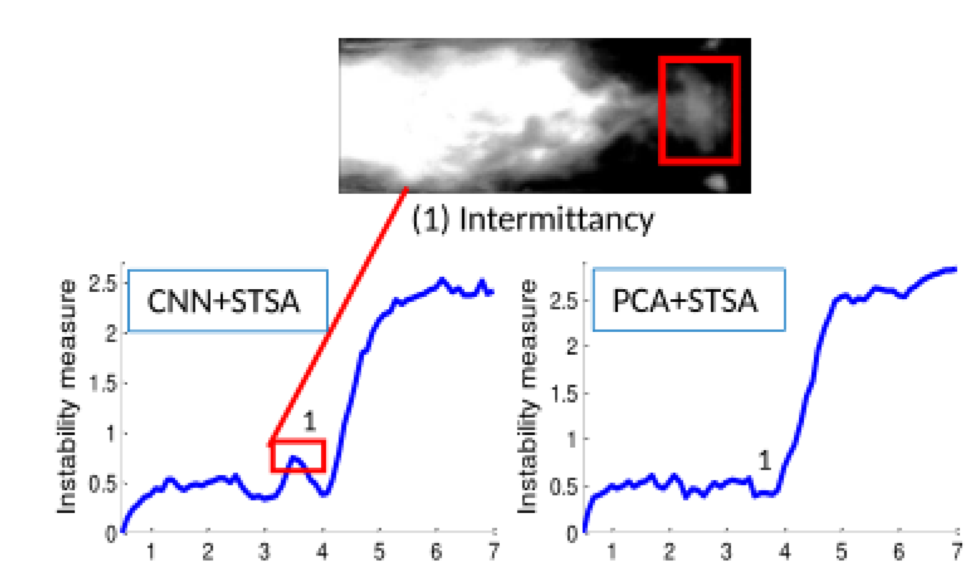

Fig 7: Variation of instability measure evaluated from both CNN+STSA and PCA+STSA. Coherent structure highlighted by box.

Conclusions & Future Work

- **Novel neural symbolic approach for complex fluid-mechanical instability problem.**
- **Semantic dimensionality reduction** via CNN, as opposed to the **abstract approach** using PCA
- Rigorous experimental validation shows **wide applicability** across various operating conditions.
- Can **involve domain experts** into data analytics seamlessly for expert-guided data exploration activities.
- **Future work** includes (1) developing novel use-cases in this neural-symbolic context, (2) dynamically tracking multiple coherent structures, (3) multi-dimensional partitioning to directly use last sigmoid layer, (4) end-to-end learning of CNN + STSA.

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