Dynamic Pressure-Based Combustion States Clustering Using Variational Auto-Encoder Method

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1 Introduction

Occurrence of combustion instability is a negative phenomenon on gas turbine field [1]. This event consequently disturbs flame stability in a gas turbine combustor. Occasionally, flashback and blowout are induced by this inherent risk. Unintended circumstances on comubstion operation mean that efficiency of gas turbine is going to be decreased, so that monitioring and diagnostics methodologies must be developed to avoid and prevent harmful incidents. Recently, various precursors had been proposed for the instability and utilization of monitoring data also highlited. For example, flame image based deep learning approach has been proposed [2-4]. Furthermore, time series dynamic pressure data preprocessed under statistical methods had also been used to detect transient combustion states [5-7]. In this research, using variational auto-encoder, 3-dimensional latent space which can be regarded as combustion states cluster is constructed and also the model analysis has been proceeded.

2 Clustering Method

In this research, 1-d convolutional variational auto-encoder method has been employed to construct a latent space which acts as a cluster of combustion states. Due to the key feature of variational auto-encoder, the dimension size of input data get reduced into 3-dimension in latent space layer. Moreover, another dimension reduction is applied on dynamic pressure data as a preprocessing step using statistical methods. The merit of these methods is that it can reduce the size of input data under the reliable rules. Following four statistical methods are the properties that make the dimension being reduced. More details are described in [8].

Root Mean Square :

$$\mathrm{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - \bar{p})^2}$$

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Where p_i is instantaneous dynamic pressure, $\bar{p}$ is mean dynamic pressure, and n is a frame size of partial dynamic pressure.

Temporal Kurtosis [6] :

$$\mathrm{TK} = \frac{\frac{1}{n}\sum_{i=1}^{n}(p_i - \bar{p})^4}{\left[\frac{1}{n}\sum_{i=1}^{n}(p_i - \bar{p})^2\right]^2}$$

Where p_i is instantaneous dynamic pressure, $\bar{p}$ is mean dynamic pressure, and n is a frame size of partial dynamic pressure.

Permutation Entropy [5] :

$$\mathrm{PE} = -\sum_{m=1}^{{}_k\mathrm{P}_{k-1}} P(\pi_m)\log_2 P(\pi_m)$$

Where $P(\pi_m)$ is sum of the permutation orderness, k is order of permutation, and P is permutation.

Zero Crossing Rate [7] :

$$\mathrm{ZCR} = \frac{1}{2N}\sum_{n=1}^{N-1}\left|S[p_i(n)] - S[p_i(n+1)]\right|$$

$$S[p_i(n)] = \begin{cases} 1, & p_i(n) \geq 0 \\ -1, & p_i(n) < 0 \end{cases}$$

Where p_i is instantaneous dynamic pressure and N is a frame size of partial dynamic pressure. Using above equations, dynamic pressure data is preprocessed into representive numbers. With operation condition, these data get converged in order as $\boldsymbol{x}_{\mathrm{n}}$.

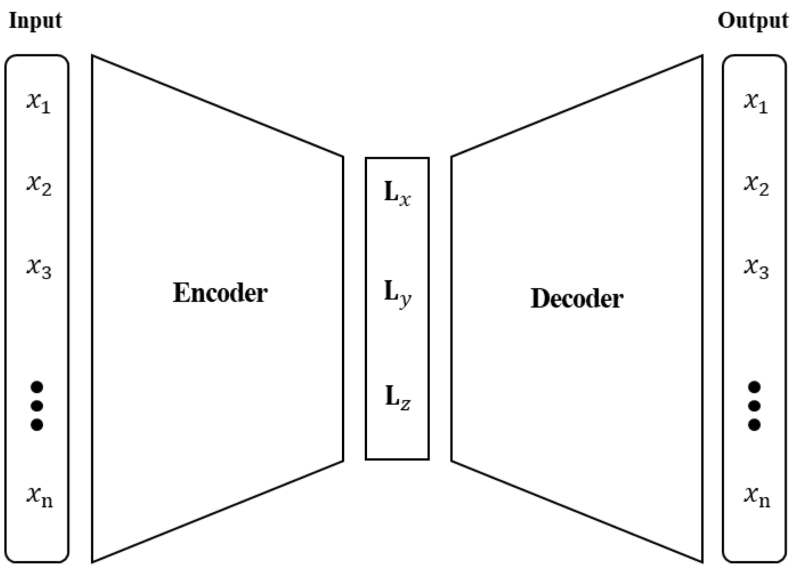

Figure 1 : Structure of variational auto-encoder with latent space variables.

3 Results

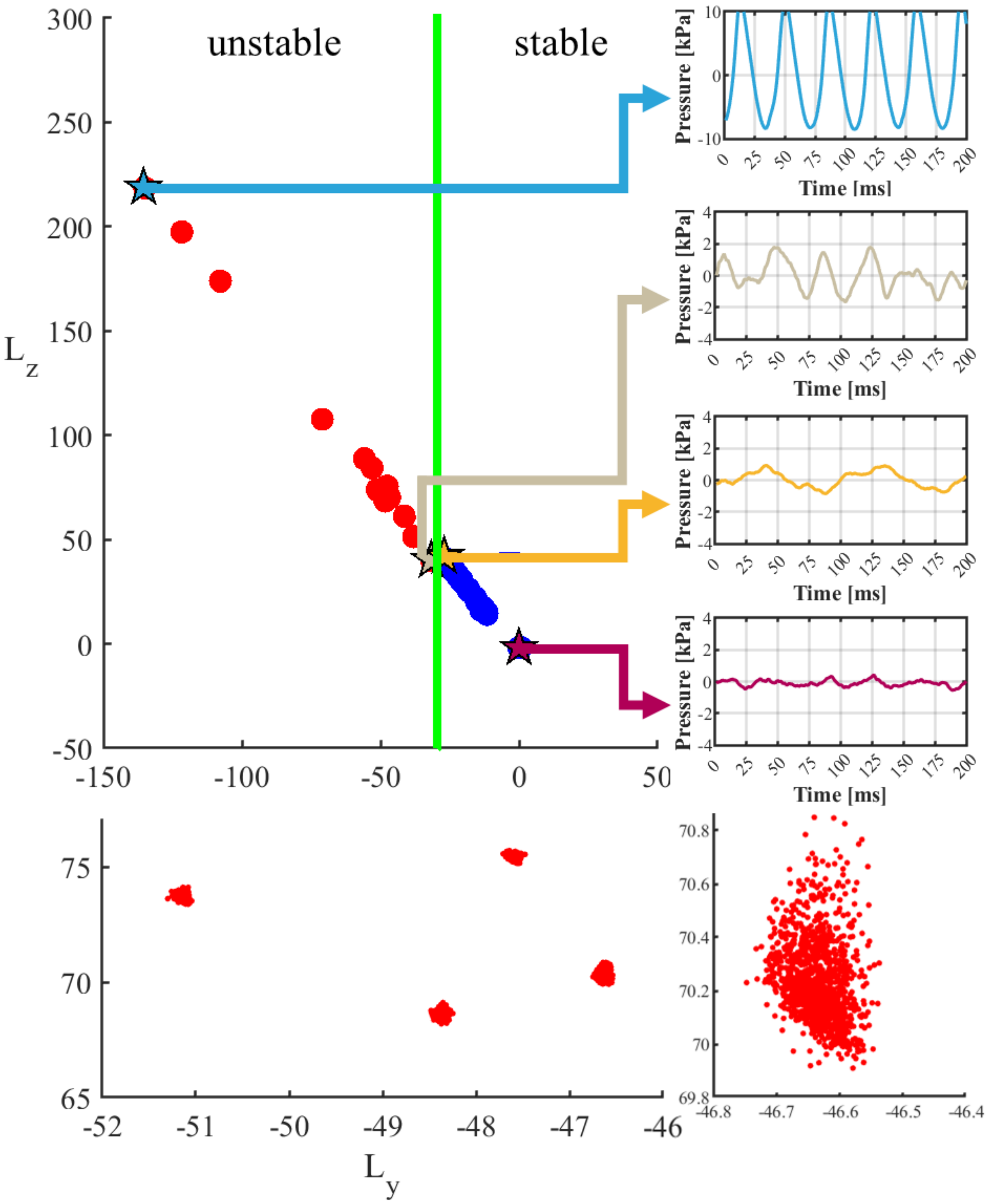

Figure 2 : Combustion States Cluster. Upper left : Latent space. Upper right : Partial dynamic pressure. Bottom : Zoomed unstable combustion states set.

4 Conclusion

Variational auto-encoder for constructing combustion states cluster has shown clear result of occurrence of combustion instability. The direct signal was preprocessed under statistical rules and combined with operation conditions. After that, it got into the model to train a latent space. As a result, the cluster has been successfully constructed. Each partial cluster has shown its character which represents activeness of its violence.

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