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Detection of Combustion Instabilities Cased by Premixed Flames Using Convolutional Autoencoder

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Abstract - In this paper, using a simple combustion device consisting of a premixed burner, a rectangular cylinder, and a visualization window, the pressure fluctuation level and fame images were measured when the flame position and operating conditions were varied. By applying a Convolutional Autoencoder (CAE) to the acquired images and extracting features, a Combustion Instability Index ($\Delta \mathrm{CAE}_{\mathrm{TI\_err}}$) was defined that can quantify flame conditions. By organizing the correlation between the proposed index and combustion oscillation levels, we evaluated the possibility of detecting signs of increased combustion oscillation. The results showed that the proposed Combustion Instability Index and the combustion oscillation level were highly correlated. The mechanism that causes the increase in combustion oscillation level was discussed by evaluating the effect of operating conditions on flame distribution using Grad-CAM data analysis, which enable visualization of the index on a two-dimensional plane.

***Keywords*:** Premixed combustion, Combustion instability, Convolutional Autoencoder, Grad-CAM

1. Introduction

To improve the reliability of combustors in gas turbines, rocket engines, it's necessary to prevent the occurrence of sudden abnormal condition by monitoring the operating conditions measured using various sensors. Research has been conducted on a method that can detect signs of combustion instability during lean combustion by measuring pressure fluctuation data inside the combustor and those data were analysed using machine learning and deep neural networks (DNN) [1][2][3].

On the other hand, not only the pressure fluctuation data but also the spatial distribution and time variation of the flame are important information to determine whether the combustion oscillation level increases or not. There are a number of studies that investigate the distribution of heating rate fluctuations and flame shape characteristics to identify signs of combustion Instability. For example, a method to directly evaluate heat release rate fluctuations has been proposed to visualize and measure the distribution of OH radicals in a flame by fluorescing them (OH-PLIF method) [4][5]. Research and other activities to monitor and classify combustion conditions and evaluate combustion instability have also been conducted actively in recent years by analysing these image data using machine learning and Convolutional Neural Networks (CNN) [6][7][8].

In this study, combustion experiments were conducted using a simple combustion device consisting of a burner with a swirler nozzle and a rectangular cylinder with a visualization window. Flame images acquired by a high-speed camera were analysed using a Convolutional Autoencoder to extract flame features. The difference between the reconstructed image based on the feature values and the input image were defined as the Combustion Instability Index, and the relationship between this index and the combustion oscillation level were discussed. In the experiment, the combustion oscillation level was measured by a pressure fluctuation sensor, and combustion experiments were conducted for several cases of varying the fuel-air ratio of the premixed air of LP gas and air.

2. Experiment Summary

2.1. Experimental device and measuring equipment

The experimental device used in this study is shown in Fig.1. A premixing nozzle with a swirler was inserted into a 50 mm square rectangular cylinder 1200 mm long, and LP gas (main component: propane) and air was supplied to the nozzle by a mass flow meter (HORIBA: S600-BM212). The combustion oscillation level was measured with a microphone (Bruel

& Kjaer: 4938) placed at the combustion cylinder inlet. The device used in this study was equipped with a visualization window to observe the flame inside the combustor, and a high-speed camera (FASTCAM: SA3 LCB) was used to take images. A high-speed camera capable of measuring monochrome images was used. The position of the pressure fluctuation resulting from the acoustic mode inside the combustor and the heat release rate fluctuation of the flame are important factors for combustion instability. The position of the visualization window can be moved in the flow direction to allow flame images to be acquired during tests in which the flame position is intentionally changed. A Malfunction (NI: USB-6251) I/O device was used to synchronize the mass flow meter, microphone, and high-speed camera outputs. A premixing nozzle with a swirler was used to ensure flame stabilization.

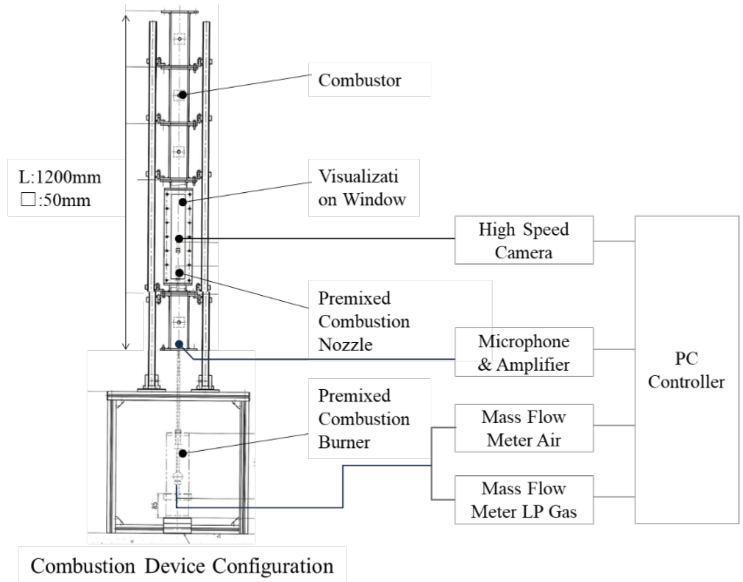

Fig.1: Simplified combustion devices and instrument

2.2. Experimental condition

In order to obtain data under various combustion conditions, the combustion oscillation level and flame image data were obtained by keeping the LP gas flow constant and changing the air flow condition step by step as shown in Table 1. The air flow rate was set to the limit of flame lift and blowout, and the gas flow rate was set to the limit considering the heat resistance of the nozzle (uncooled). As shown in the left of Fig.2, the nozzles were positioned at L/2, L/4, and L/8 from the bottom (upstream) end of the cylinder relative to the total length of the combustion cylinder (L). The flame position was varied in order to investigate the effect of the relationship between the antinode, node, and midpoint of the first-order acoustic mode generated in the combustor and the location of the flame on the level of combustion oscillation. The air flow rate was controlled sequentially as shown in the right of Fig.2.

Table1: Experimental parameters

Case No.	Flame Position [−]	LP Gas flow rate [L/min]	Air flow rate [L/min]
POS①_Case1	①	0.3	0 → 4.0
_Case2	↑	0.5	0 → 8.4
_Case3	↑	0.8	0 → 14.2
_Case4	↑	1.0	0 → 15.0
_Case5	↑	1.2	0 → 16.6
POS②_Case1	②	0.3	0 → 4.0
_Case2	↑	0.5	0 → 8.4
_Case3	↑	0.8	0 → 14.2
_Case4	↑	1.0	0 → 15.0
_Case5	↑	1.2	0 → 16.6
POS③_Case1	③	0.3	0 → 4.0
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_Case4	↑	1.0	0 → 15.0
_Case5	↑	1.2	0 → 16.6

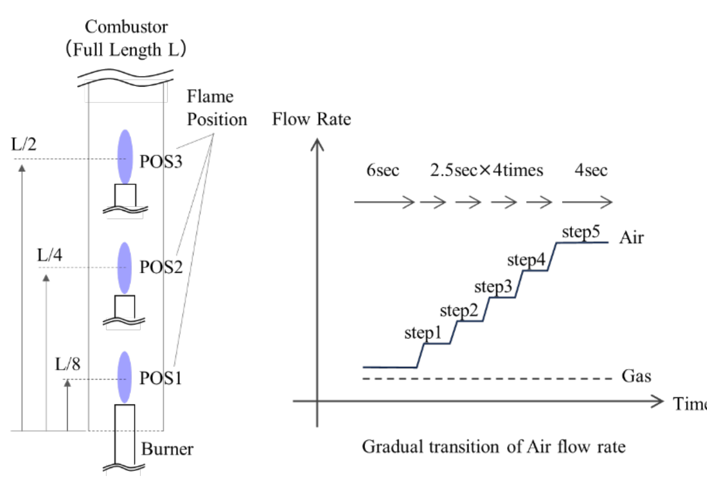


Fig.2: Burner position and operating condition

2.3. Equipment Characteristics

An example of the measurement data obtained from the combustion experiment is shown in Fig.3. The air flow rate was was increased stepwise at 7 seconds after starting the combustion operation sequence, and the combustion oscillation level level tended to increase gradually as the air flow rate increased. The maximum combustion oscillation level occurred approximately 20 seconds after the start of the step change in air flow rate. The image taken by the high-speed camera (20 (20 seconds after the start of the sequence) is shown on the right of Fig.3. In the early period after the start of the combustion combustion operation sequence, the air flow rate is low, resulting in an orange flame due to thermal radiation from carbon particles (soot particles) generated by the decomposition of hydrocarbons, but as the air flow rate is gradually increased, the flame becomes blue-white due to emission of unstable radicals. The orange flame under low air flow rate conditions will show relatively white when viewed in a monochrome image from a high-speed camera. The image on the right of Fig.3 shows a bluish-white flame at a timing of high air flow rate, indicating that the white area is the high-temperature combustion zone.

Frequency analysis of the combustion oscillation generated by the combustion device used in this study confirmed that there is a peak at 158 Hz. 158 Hz is considered to be generated by the open-open acoustic first-order mode (half wavelength) generated by this combustion device, and the average sound velocity inside the combustion device is estimated to be 379 [m/s] and the average temperature is 104 [°C].

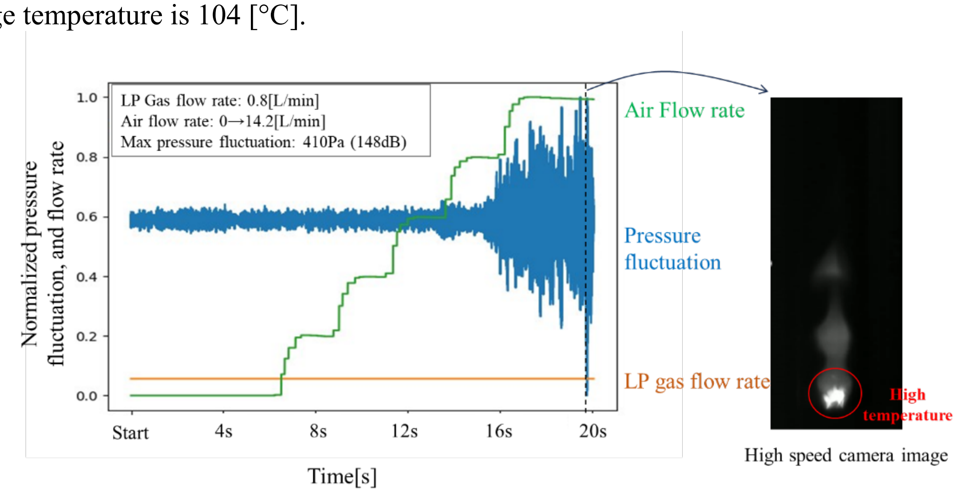


Fig.3: An example of measurement results (POS3_Case3)

3. Data Analysis Methods

3.1. Convolutional Autoencoder (CAE)

Convolutional Autoencoder (CAE) is a type of Deep Learning that combines an Autoencoder and a Convolutional Neural Network (CNN) for feature extraction of data [9]. In this study, CAE models were built using flame images taken by a high-speed camera during normal operation. CAE data analysis was then performed on all measured data, and an attempt was made to discriminate abnormal conditions by evaluating the differences between input and output images. The cases with small combustion oscillation levels (from POS1 to POS3) were used as training data for the detection of abnormal conditions.

The evaluation methods for combustion instability using CAE are shown in Fig.4 and Eqs. (1) - (3) below. In the first method, as shown in left of Fig.4 and Eqs. (1), the time variation value ($\Delta\mathrm{CAE_{err}}$) of the residual sum of squares of the luminance (x_{in}) in the input image and (x_{out}) after CAE analysis is defined as the Combustion Instability Index. The second method was focused on the interval corresponding to the sequential control of air flow as shown in right of Fig.4 and Eqs. (2), and was defined the amount of change in each interval as ($\Delta\mathrm{CAE_{TI\_err}}$). In the results and discussion in Chapter 4, we confirm the validity of the evaluation index proposed in this study by comparing it with the Combustion Instability Index calculated by the conventional evaluation method ($\Delta\mathrm{Im_{TI\_err}}$) as Eqs. (3), which does not use CAE.

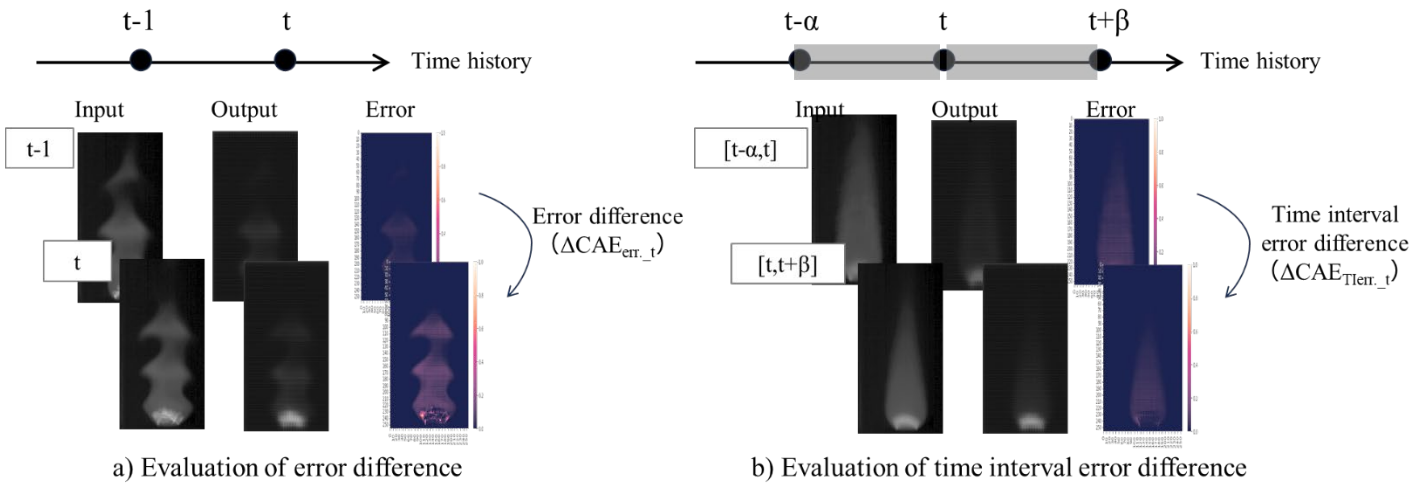


Fig.4: Quantitative evaluation of combustion instability by using CAE

$$\Delta\mathrm{CAE}_{\mathrm{err}} = \sum_{i=1}^{n}\left(x_{\mathrm{i}_{\mathrm{out}_{\mathrm{t}}}} - x_{\mathrm{i}_{\mathrm{in}_{\mathrm{t}}}}\right)^2 - \sum_{i=1}^{n}\left(x_{\mathrm{i}_{\mathrm{out}_{\mathrm{t-1}}}} - x_{\mathrm{i}_{\mathrm{in}_{\mathrm{t-1}}}}\right)^2 \tag{1}$$

$$\Delta\mathrm{CAE}_{\mathrm{TI\_err}} = \sum_{j=t-\alpha}^{t}\sum_{i=1}^{n}\left(x_{\mathrm{i}_{\mathrm{out\_j}}} - x_{\mathrm{i}_{\mathrm{in\_j}}}\right)^2 - \sum_{j=t}^{t+\beta}\sum_{i=1}^{n}\left(x_{\mathrm{i}_{\mathrm{out\_j}}} - x_{\mathrm{i}_{\mathrm{in\_j}}}\right)^2 \tag{2}$$

$$\Delta\mathrm{Im}_{\mathrm{TI\_err}} = \sum_{j=t-\alpha}^{t}\sum_{i=1}^{n}\left(x_{\mathrm{i}_{\mathrm{in\_j}}}\right) - \sum_{j=t}^{t+\beta}\sum_{i=1}^{n}\left(x_{\mathrm{i}_{\mathrm{in\_j}}}\right) \tag{3}$$

n: Number of pixels in the image, α: Number of samples in the time interval before t, β: Number of samples in the time interval behind t, x: Luminance (normalization:0-1)

This study investigated the relationship between the Combustion Instability Index calculated from the image data analysis described above and the level of pressure fluctuation. In this study, combustion experiments were conducted with sequential control of air flow rate, and it's considered that the Combustion Instability Index also changes in steps according to the change in air flow rate. As shown in Fig.5, the Combustion Instability Index ($\Delta\mathrm{CAE}_{\mathrm{err}}$), indicated by the red line defined as Eqs. (1) is a large change around intervals from TI6 to TI8. The Combustion Instability Index tends to change significantly around intervals 6 to 8.

As shown in Fig.6, the combustion oscillation level was evaluated as the average of the five maximum values of the pressure fluctuation level in each case. The pressure fluctuation level was evaluated by the absolute value of amplitude. By evaluating the correlation between the Combustion Instability Index and the pressure fluctuation level for each section, we discussed in Chapter 4 whether the information obtained from the flame image could detect signs of increased pressure fluctuation. The time difference between the time of occurrence of combustion instability and the end of the time interval was defined as the margin of abnormality detection ($\mathrm{t_a}$), which was used as an index to evaluate how much margin there is against the point of occurrence of increased combustion oscillation in Chapter 4.

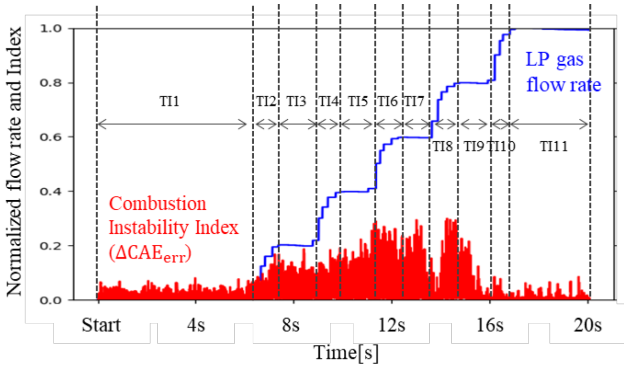


Fig.5: Definition of Time interval (TI) and Combustion Instability Index

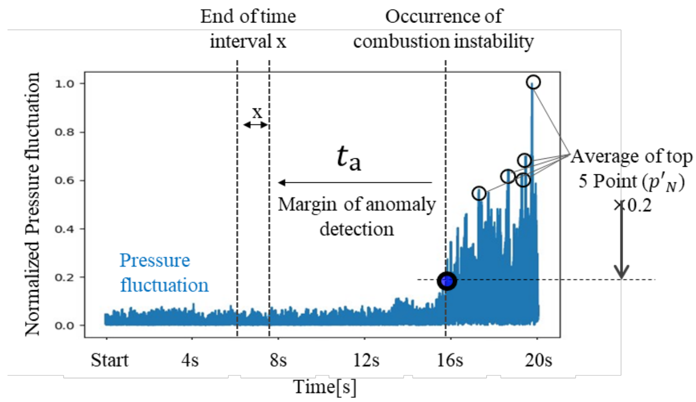


Fig.6: Evaluation of pressure fluctuation level and anomaly detection time

3.2. Gard-CAM

In this study, the Grad-CAM method [10] was applied to visualize which parts of the image were affected by the model in the feature extraction process by CNN as shown in section 3.1. The heatmap output shows the areas that affected the output value (S_c) by multiplying the features (A_{xy}^k) output by the gradient (α_c^k) obtained by back-propagation. The calculation equation is shown in Eqs. (4).

$$\mathrm{M}_{\text{Grad-CAM}}(x,y) = \mathrm{ReLU}\left(\sum_k \alpha_\mathrm{c}^\mathrm{k} A_\mathrm{xy}^\mathrm{k}\right) \tag{4}$$

$$\alpha_\mathrm{c}^\mathrm{k} = \frac{1}{Z}\sum_{x,y}\frac{\partial S_\mathrm{c}}{\partial A_\mathrm{xy}^\mathrm{k}}, F^\mathrm{k} = \frac{1}{Z}\sum A_\mathrm{xy}^\mathrm{k}, S_\mathrm{c} = \sum_k \omega_\mathrm{c}^\mathrm{k} F_\mathrm{c}^\mathrm{k}$$

k : Output of convolutional layer, A_xy^k : Features at position x, y, z : Number of pixels in feature map, $\omega_\mathrm{c}^\mathrm{k}$: Weight parameter connecting output and input, S_c : Output at class c

As shown in Fig.7, this study focused on the gradient between the output of the convolution layer of the encoder section and the residual sum of squares calculated by Eqs. (2), and attempted to visualize in a heat map the part that affected the data analysis results. The state change of Combustion Instability Index (ΔCAE_{TI_err}) is evaluated in the CAE data analysis, and in the evaluation using Grad-CAM shown in this chapter, the amount of change in the average value of each interval shown in Eqs.(5) was also incorporated as an evaluation method so that the state of change in the area that affected the data analysis can be evaluated using image distribution.

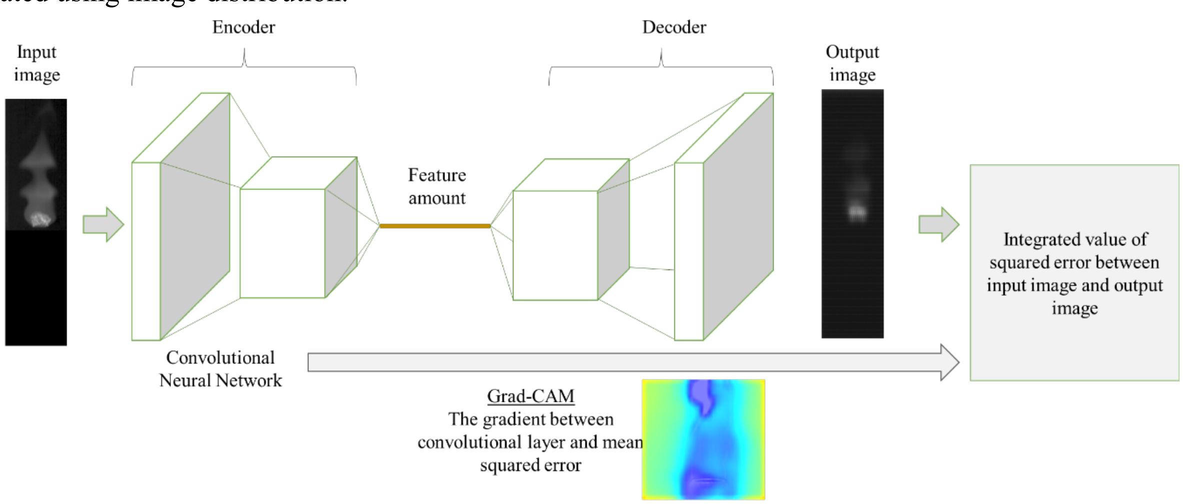


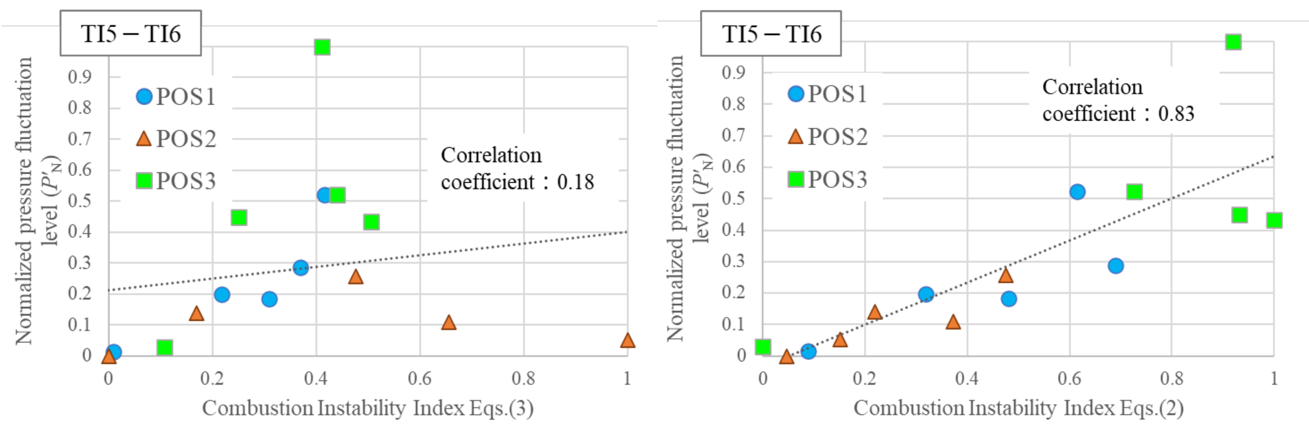
Fig.7: Definition of Grad-CAM in this study

$$\Delta \mathrm{M}_{\text{Grad-CAM}_{\text{TI\_i}}} = \frac{1}{\alpha}\sum_{j=t-\alpha}^{t}\left(\mathrm{M}_{\text{Grad-CAM\_j}}\right) - \frac{1}{\beta}\sum_{j=t}^{t+\beta}\left(\mathrm{M}_{\text{Grad-CAM\_j}}\right) \tag{5}$$

α: Number of samples in the time interval before t, β: Number of samples in the time interval behind t

4. Results and Discussion

Data analysis of all cases was performed using the CAE evaluation method shown in section 3. Fig.8 shows the relationship between the pressure fluctuation level and the combustion instability level calculated from flame images in time interval from 5 to 6. The left figure a) plots the average of the luminance change of the high-speed camera image calculated from the conventional index $\Delta \mathrm{Im}_{\text{TI\_err}}$ as shown in Eqs. (3) and the oscillation level of the top five points. The right figure b) plots the Combustion Instability Index ($\Delta \mathrm{CAE}_{\text{TI\_err}}$) calculated from Eqs. (2) proposed in this study and the average value of the combustion oscillation level of the top five points. The proposed Combustion Instability Index has a correlation coefficient of 0.83, which indicates that it can detect the onset of combustion oscillation level better than conventional method.



a) Evaluation using conventional index $\Delta \mathrm{Im}_{\text{TI\_err}}$

b) Evaluation using the new proposed index $\Delta \mathrm{CAE}_{\text{TI\_err}}$

Fig.8: Relationship between Combustion Instability Index and pressure fluctuation level in time interval from 5 to 6

Fig.9 shows the results of correlation analysis between Combustion Instability Index ($\Delta \mathrm{CAE}_{\text{TI\_err}}$) and combustion oscillation level for all data. The method proposed in this study tends to show higher correlations in all time intervals than the conventional method. In addition, according to the definition shown in Fig.6, the relationship between the interval from 5 to 6 and the oscillation increase start time were analysed in order to quantitatively evaluate how many seconds before the start of oscillation increase it's possible to detect the signs of oscillation increase. The results of the data analysis for all data (Fig.10) showed that the most frequent value of the detection time was from 5 to 6 seconds. Based on the above results, the Combustion Instability Index ($\Delta \mathrm{CAE}_{\text{TI\_err}}$) proposed in this study is an effective evaluation index that can detect signs of increased oscillation in advance.

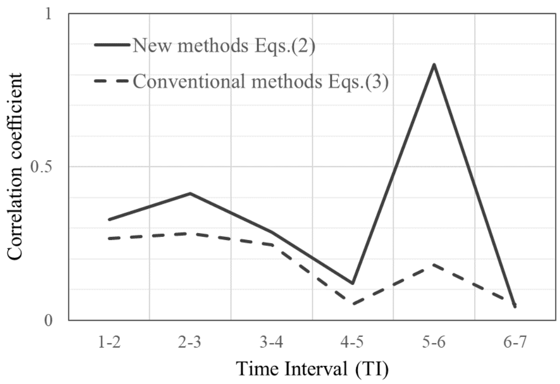


Fig.9: Relationship between time interval and correlation coefficient

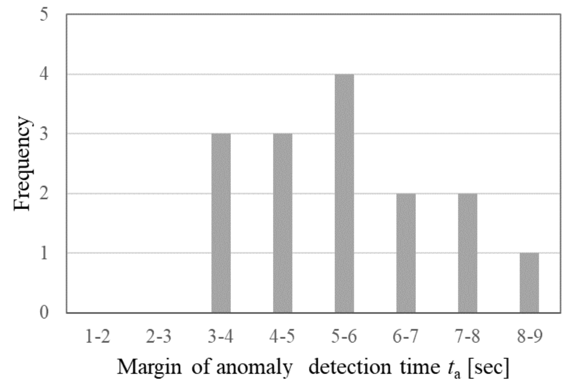


Fig.10: Relationship between time interval and detection time (t_a)

Next, we attempted to identify the elements in the image that have a significant impact on Combustion Instability Index by analysing the data using Grad-CAM as described in section 3.2. In this data analysis, the evaluation index shown in Eqs.(5) was used. As in the evaluation of the Combustion Instability Index, we focused on the amount of change in the interval mean in the Grad-CAM.

In the Grad-CAM image shown in the left of Fig.11, the inner flame near the nozzle outlet and the outer flame at the edge of the flame tend to be coloured red. Focusing on the flame position of Pos3 shown in right of Fig.11, the red area shifts from the outer flame to the inner flame as the air flow rate is increased in the order of Case 2 to 5. Since the combustion oscillation level reaches its maximum in Case 3 at the middle air flow rate, there is a possibility that there is a singularity where the coupling between combustion flame and acoustic mode is promoted and the oscillation increases during the transition process of air flow rate change. Qualitatively, the Combustion Instability Index increases as the combustion oscillation level increases in the order of POS2, POS1, and POS3, as shown the coloured circle in the left figure, suggesting that the evaluation index for combustion instability proposed in this study is effective.

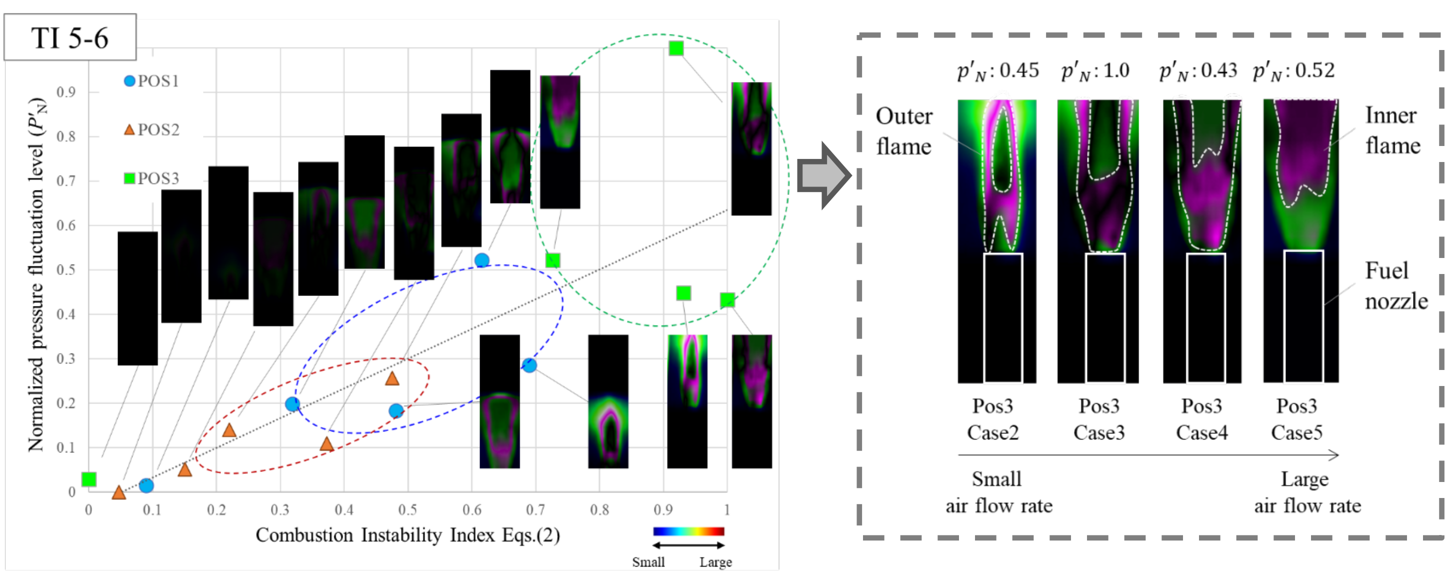


Fig.11 Evaluation of influence by using Grad-CAM（$\Delta M_{\text{Grad-CAM}_{\text{TI}\_i}}$）

5. Conclusion

In this study, in order to understand combustion instability phenomena in a simple way, the pressure fluctuation and combustion flame images in various operations were measured using a simple combustion device consisting of a with a nozzle with a swirler and a rectangular cylinder with a visualization window. We focused on the flame images with a high-speed camera, we used the Combustion Instability Index (ΔCAE_{TI_err}) calculated from Convolution (CAE) analysis and discussed its relationship with the combustion oscillation level. At the same time, we applied the CAM data analysis method to visualize which part of the image is focused on in the feature extraction process for the Convolutional Neural Network (CNN) used in the calculation process of the Combustion Instability Index (ΔCAE_{TI_err}). The correlation between the Combustion Instability Index (ΔCAE_{TI_err}) and the combustion oscillation level proposed in this study is as high as 0.83, indicating the possibility of detecting the increasing trend of combustion oscillation level in advance. The results of the Grad-CAM data analysis, which allows visualization of the influence on the Combustion Instability Index (ΔCAE_{TI_err}), confirmed a tendency for the influence rate to shift from the outer flame to the inner flame with increasing air flow rate. Although there is a singular point where the combustion oscillation level increases with a specific air flow rate, qualitatively, the evaluation index for combustion instability proposed in this study was confirmed to be valid.

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