VORTEX SHEDDING CHARACTERISTICS OF PREMIXED FLAME

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DATA OVERVIEW:

Premixed methane and air mixture flame images taken at 10,000 FPS (frames per second), through which OH chemiluminescence is captured. 17 such sets of data, each with individual Equivalence ratio and a Reynolds number, both as Images series and corresponding data time series were shared with us. Image Scaling: 5px/mm.

OBJECTIVE:

- Using Image Series, with two independent variables (equivalence ratio and Reynolds number) and evaluating our two dependent variables (flame flickering height and dominant flickering frequency), we are clustering the dataset into 2 major cases: whether flickering is happening or not.
- Using the data-time series, to find the correlation between OH chemiluminescence and flame flickering height.

METHODOLOGY AND OBSERVATIONS:

IMAGE PRE-PROCESSING

We had an entirely black image to start with, and to observe the image, we had various methods to change the contrast like CLAHE *(Contrast limited adaptive histogram equalization),* imadjust and finally, binarizing. We found binarizing was an apt option, after which we had cropped, flattened into column matrices and finally combined into one big image_matrix.

PROPER ORTHOGONAL DECOMPOSITION:

Using the obtained image_matrix we performed POD on all 17 datasets of images individually. We observed a major trend from all the entire dataset of images: In some cases, the "Vortex Shedding" was observed, while others had just noisy "Flame tip Oscillations". We were able to understand the physical interpretation of each POD mode as follows.

POD MODE	SIGNIFICANCE
1^{ST}	Overall Intensity map of the flame
2^{ND}	Vortex Shedding / Major flickering dynamics
3^{RD}	Minor Flickering Dynamics

Following this, we performed FFT using 5^{th} rank approximated image to calculate the frequency, clearly indicated notable frequency with a peak for flickering frequency dataset, while a noisy frequency distribution otherwise. The flame height was evaluated by binarizing the first POD mode with a suitable threshold.

DYNAMIC MODE DECOMPOSITION:

By performing DMD on image_matrix, we obtained the first few dominant dynamic spatial modes. Also we were able to predict the next image. We studied non-linearity vs DMD, by testing various well-known linear and non-linear systems to understand when DMD will work its best and when it is not that accurate.

CLUSTERING:

Once after calculating the frequencies and height from all the 17 datasets, we plotted a map between the dependent variables and the independent ones and clustered them majorly into cases where flickering occurs and where not.

DATA PROCESSING:

Upon visualizing the data, it was discovered that the OH chemiluminescence and the flame tip location are likely to be strongly related whenever there is flickering. But calculating the correlation of noisy time-series data might give a wrong result. So, several smoothening (noise removal) processes were tried and compared.

SMOOTHENING

The moving window average is first eliminated as it did not produce as good a smooth curve as SG filtering. Further, the optimal parameters of SG and Gaussian filters (window size, polynomial order for the SG and variance for the Gaussian) with the highest signal-to-noise ratio and the second derivative bounded within its standard deviation were found. Reflect padding was used in Gaussian filtering. It was found that the Gaussian filtering produced a smoother curve with a slightly lower signal to noise ratio compared to SG filtering and had minimal change in amplitude of the signal. Therefore, the Gaussian filtered data was chosen to be correlated.

CORRELATION

1. For the flickering case, there is a clear correlation (with a coefficient of 0.5) between the chemiluminescence and the flame tip location although with a phase delay between the flame tip and the luminescence which is an indication of heat release rate. The phase lag is a new observation and may reveal some new insights upon further exploration.

2. For the case with no flickering, correlation coefficient of 0.28 was obtained for the noisy data while the smoothened data showed nearly zero correlation. This helps us to understand the role of noise fluctuations in the flame tip, corrupting the correlation calculations in the raw data. Hence careful judgement on which filters are to be used and how they are implemented is of paramount importance.

REFERENCES

1. J. Nathan Kutz et.al., Dynamic Mode Decomposition: Data-Driven Modeling of Complex Systems
2. Akhil Aravind et al., Response of premixed Jet Flames to Blast Waves