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Detection of flame wrinkling in spherically expanding flames using time series classification with pressure traces

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Abstract: Intrinsic instabilities in spherically expanding flames often manifest as cellular structures on the flame surface. In the case of spherically expanding flames, they have been extensively studied visually using high speed cameras in conjunction with optical diagnostic techniques. While pressure traces of the combustion event are often used to characterize non-intrinsic flame instabilities (e.g., thermoacoustic), they are significantly less explored with respect to intrinsic instabilities for spherical flames. This work investigates the potential for the detection of wrinkling of spherically expanding flames using time series classification (TSC) with pressure traces. The data set contained 386 time series samples (pressure traces) that were labeled based on the associated high-speed images. The dataset contained flames from mixtures that vary in terms of fuels, working fluids, initial pressures, and equivalence ratios. A high classification accuracy ($>$ 93%) was obtained with an ensemble machine learning algorithm for TSC, though a preliminary exploration did not yield any clear classification features and indicates the need for further exploration.
***Keywords:* intrinsic instability, spherical flame, time series classification, pressure trace, constant volume combustion chamber**

1. Introduction

Combustion instabilities are physical phenomena that exacerbate small disturbances in a combustion system into larger ones. They are often classified into being intrinsic, chamber, and system instabilities. Intrinsic instabilities amplify perturbations in the flame front due to the innate properties of the combustible mixture. They are of interest when the fundamental combustion of a mixture is studied without reference to a specific combustor or system design. They have been studied for decades due to their fundamental nature as well as potential effects on other combustion properties [1]. Multiple theoretical models have been devised over the years to explain the wrinkling of flames due to these intrinsic instabilities [2]. Most commonly, intrinsic instabilities are either hydrodynamic effects or thermal-diffusive. Their nature and extent depend on several factors such as thermal expansion, flame thickness, Lewis number, and activation energy [3].

A constant volume combustion chamber (CVCC) is a canonical device used to study fundamental combustion behaviors. In its most common configuration, a CVCC is filled with the combustible mixture of interest and ignited at the center using opposed electrodes. This results in the creation of spherically expanding flames. CVCCs with optical access can be used to record high-speed images of the flame, often in combination with advanced imaging techniques such schlieren or shadowgraph imaging. These images show the flame fronts due to density gradients and the perturbations in the flame fronts appear as ‘wrinkles’ in the flame front, which may form cells, as illustrated in Fig. 1. Most studies that employ CVCCs to study instabilities use such high speed images of the spherical flames for either simple detection or qualitative/quantitative characterization of surface features such as cell density or crack length [4]. This provides a direct and intuitive way of studying intrinsic instabilities. However, this method is limited to systems with optical access.

This study investigates the use of pressure data from a CVCC captured during spherically expanding flame experiments to detect intrinsic instabilities. Since wrinkling of the flame front can affect combustion behavior, it is likely that some artifact (or artifacts) in the pressure traces would indicate the presence of intrinsic instabilities. Pressure is a more prominent feature in the prediction and detection of of other types of instabilities, most notably thermoacoustic [5].

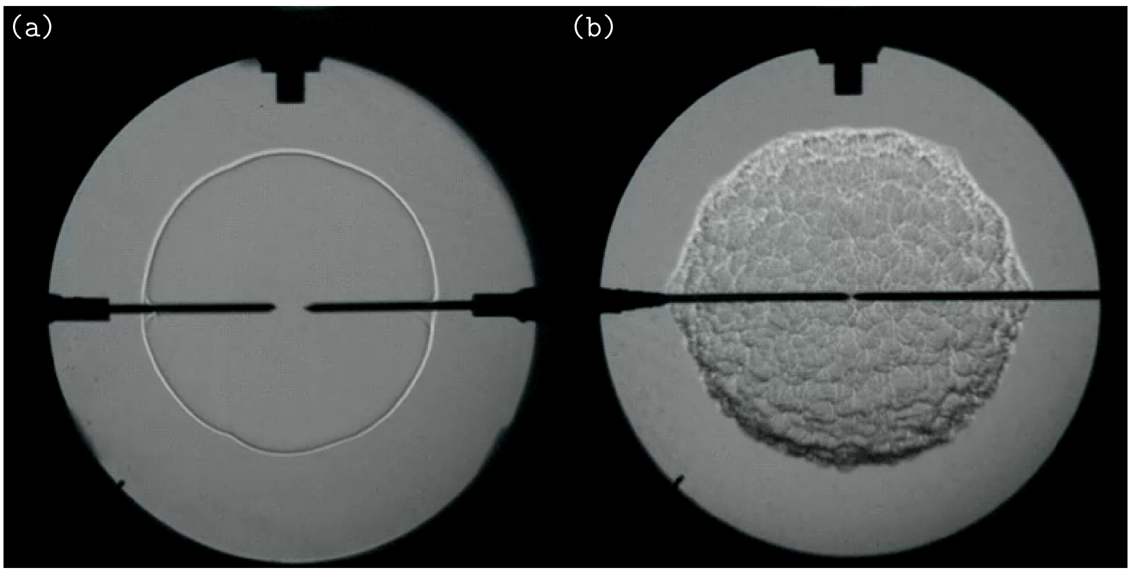

Figure 1: Spherical flame with (a) no wrinkles, illustrating a stable flame front and (b) extensive wrinkling, showing an intrinsically unstable flame.

2. Methodology

This study’s approach involved the collection and labeling of time series data for CVCC experiments, followed by the use of time series classification (TSC) algorithms for the detection of instabilities from the pressure-time data. The data used for this study was collected from several independent combustion studies over the course of three years with disparate experimental focuses as presented in previous literature [6–9]. There are 7 different fuel-oxidizer-working fluid combinations, over different equivalence ratios, fuel fractions, and initial pressures (Table 1). The mixtures were prepared in an optically accessible CVCC before ignition was initiated at the center. Details of the CVCC, imaging system, and in-depth discussion of the approach is further detailed in Ref. [10]. Pressure was recorded for spherically expanding flames at time steps of 1ms, along with schlieren videos captured using a high-speed camera. Ten pressure traces included in this study are shown in Figure 2, with further discussion on their interpretation included in Section 3.

Table 1: Pressure time series dataset and its classes (before data augmentation)

Mixture	Total samples	Instabilities	No instabilities
$NH_3-H_2-O_2-N_2$	122	25	97
$H_2-O_2-CO_2$	59	59	0
$CH_4-C_2H_4-C_2H_6-O_2-N_2$	9	0	9
$CH_4-H_2-NH_3-O_2-N_2$	28	0	28
$CH_4-O_2-N_2$	31	0	31
CH_4-O_2-Ar	29	5	24
CH_4-O_2-Kr	20	16	4
Total	298	105	193

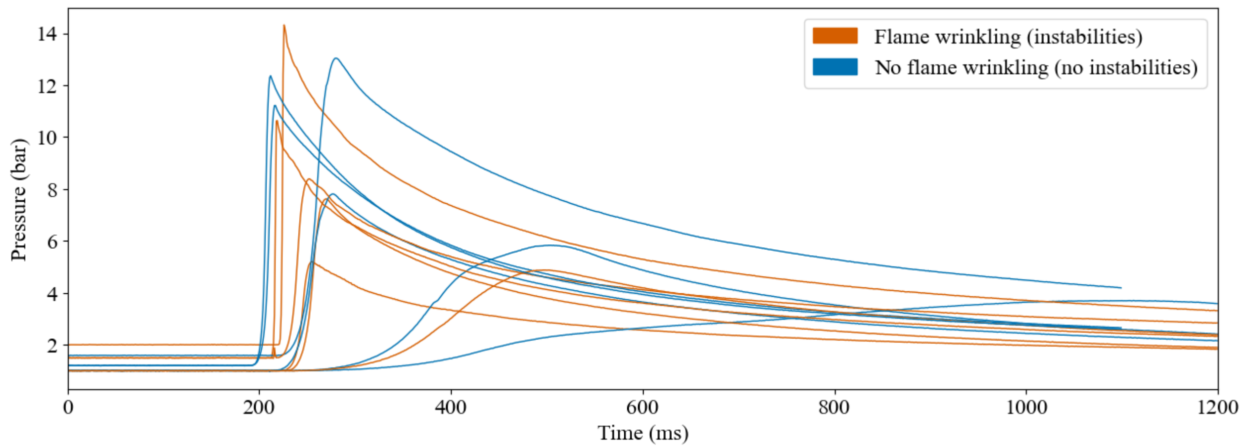

Figure 2: Illustration of pressure traces from the CVCC. The pressure traces do not provide any features that allow the naked eye to distinguish between wrinkled and non-wrinkled flames.

Each time series sample was labeled as either having cellular instabilities or no instabilities, based on a visual inspection of the flame's expansion in conjunction with an automated image processing method [6]. As seen in Table 1, there was a class imbalance in the original dataset with more samples in the 'no instabilities' class than the 'instabilities' class. To avoid the bias this could introduce towards the majority class [11], 88 samples from the minority class (instabilities) were duplicated into the data set. This made the total samples in the data set equal to 386, equally divided between both classes. The pressure traces were first explored in terms of more direct and interpretable parameters; the pressure trace, the peak pressures (P_{max}), maximum pressure rise rate $\left(\left(\frac{dP}{dt}\right)_{max}\right)$, and the dynamic time warping (DTW, a measure of similarity for time series which accounts for different speeds) score of the pressure traces. After that, an ensemble TSC algorithm, "HIVE-COTE" v2 (Hierarchical Vote Collective of Transformation-based Ensembles) [12] was tested, using its implementation in the “aeon" [13] library for time series data, with a train-test split of 80-20.

3. Results and Discussion

As shown in Figure 2, there is no clear pattern to distinguish between flames with or without instabilities from their pressure traces with the naked eye. Furthermore, Figure 3, shows that neither P_{max} and $\left(\frac{dP}{dt}\right)_{max}$ give any clear indications of instabilities. The DTW scores were calculated 'pairwise' for all samples. If the DTW can capture the difference between samples well, the distance between samples of different classes would be higher, whereas that of the same class would be lower. However, when viewed as a heatmap in Figure 4(a) (higher distances are brighter and lower distances are darker), this pattern doesn't emerge. (The repetitive pattern in the instabilities class is due to data duplication carried out during data augmentation.)

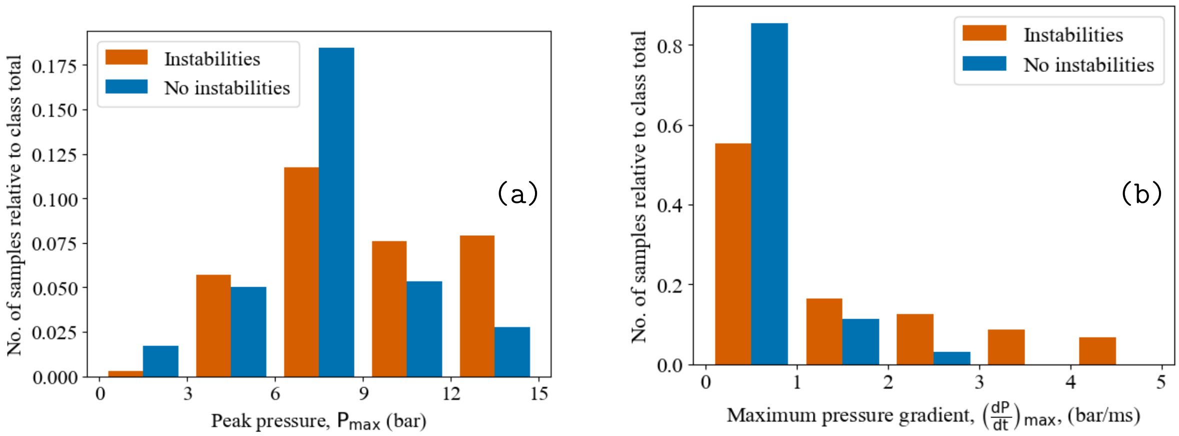

Figure 3: Distribution of maximum pressure (a) P_{max}, and (b) $\left(\frac{dP}{dt}\right)_{max}$ for each class, across the 298 samples of the dataset before augmentation.

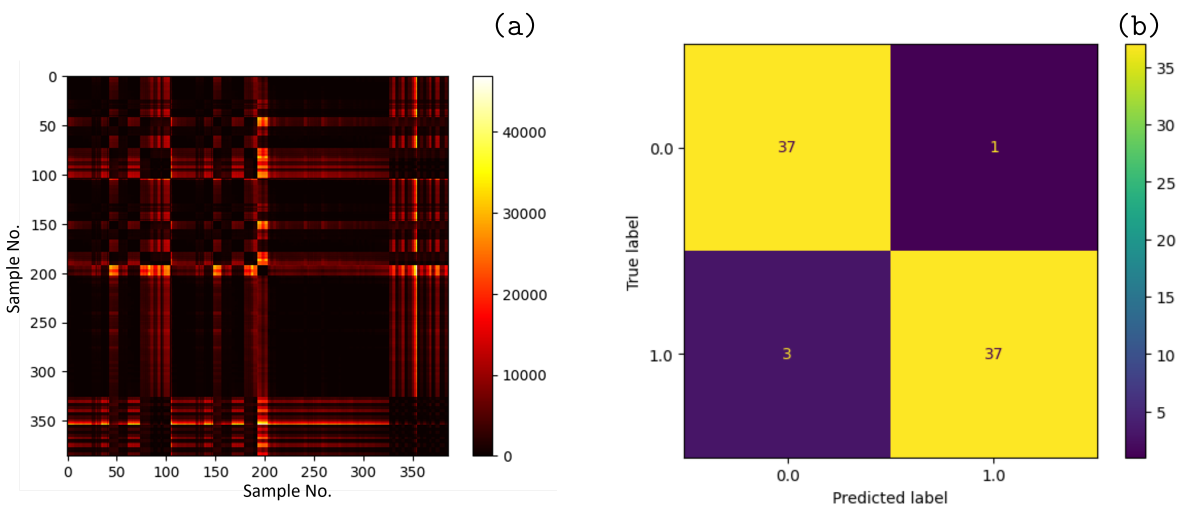

Figure 4: (a) Pairwise DTW distance between the samples in the data set. Samples 0-192 had instabilities, 193-385 did not. (b) Confusion matrix for classification performance of HIVE-COTE classifier. (Label 0 represents no instabilities, 1 instabilities)

The classification accuracy for HIVE-COTE algorithm was 94.9%. The confusion matrix in Figure 4(b) for HIVE-COTE shows its classification performance with respect to both classes, with very few false positives and negatives. As HIVE-COTE uses a weighted ensemble of TSC models, it could allow it to use patterns detected in multiple different representations within those models. However, due to the inherent lack of explainability, it is difficult to say with certainty. Considering the accuracy obtained here, HIVE-COTE could be used potentially for detecting intrinsic combustion instabilities in spherical flames with pressure traces from CVCCs. The performance of the classification algorithm is encouraging and has room to be further explored in terms of more exhaustive fine tuning, testing of other TSC models, and the use of larger datasets.

4. Conclusions

This study explored the use of a time series classification algorithm for predicting flame wrinkling in spherically expanding flames in a CVCC from their pressure data, with a reasonably high accuracy of 94.9%. It could be used to detect flame wrinkling in CVCCs that do not have optical access. This work may be extended in several different directions. The tuning of the classification algorithms' parameters could be explored in more detail to improve performance. Further exploration of the data in conjunction with other algorithms would also be important to determine what features the algorithms are picking out to classify the time series and whether these features could be generalized to get a better understanding about the direct relation of the pressure in the chamber with the intrinsic instabilities. Another interesting, but challenging proposition, could be detecting the extent of flame wrinkling and cellularization from pressure traces.

References

[1] G. H. Markstein, Experimental and Theoretical Studies of Flame-Front Stability, J. Aeronaut Sci 18 (1951) 199–209. DOI: 10.2514/8.1900.

[2] R. Addabbo, J. Bechtold, and M. Matalon, Wrinkling of spherically expanding flames, Proc. Combust. Inst. 29 (2002) 1527–1535. DOI: 10.1016/S1540-7489(02)80187-0.

[3] O. Kwon, G. Rozenchan, and C. Law, Cellular instabilities and self-acceleration of outwardly propagating spherical flames, Proc. Combust. Inst. 29 (2002) 1775–1783. DOI: 10.1016/S1540-7489(02)80215-2.

[4] M. Reyes, R. Sastre, F. Tinaut, and J. Rodríguez-Fernández, Study and characterization of the instabilities generated in expanding spherical flames of hydrogen/methane/air mixtures, Int. J. Hydrog. Energy 47 (2022) 22616–22632. DOI: 10.1016/j.ijhydene.2022.05.063.

[5] J. O. Chandrachur Bhattacharya and A. Ray, Data-driven Detection and Early Prediction of Thermoacoustic Instability in a Multi-nozzle Combustor, Combust. Sci. Technol. 194 (2022) 1481–1512. DOI: 10.1080/00102202.2020.1820495.

[6] B. Nawaz, M. N. Nasim, S. K. Das, D. Assanis, J. P. Trelles, N. Van Dam, and J. H. Mack, Optical Characterization of cellular instabilities in spherically expanding ammonia-hydrogen flames, 13th US National Combustion Meeting, College Station, TX, USA (2023), DOI: 10.31224/3018.

[7] J. H. Mack, M. N. Nasim, B. Nawaz, and S. K. Das, Effect of Products of Catalytic Oxidative Coupling on the Laminar Burning Velocity of Methane, 13th US National Combustion Meeting, College Station, TX, USA (2023), DOI: 10.31224/3016.

[8] M. Morovatiyan, M. Shahsavan, J. Aguilar, M. Baghirzade, and J. H. Mack, An assessment of hydrogen addition to methane combustion with Argon as a working fluid in a constant volume combustion chamber, Combust. Sci. Technol. 194 (2022) 2395–2413. DOI: 10.1080/00102202.2020.1870454.

[9] M. Baghirzade, M. N. Nasim, B. Nawaz, J. Aguilar, M. Shahsavan, M. Morovatiyan, and J. H. Mack, Analysis of premixed laminar combustion of methane with noble gases as a working fluid, ASME Internal Combustion Engine Forward Conference (2021), DOI: 10.1115/ICEF2021-67516.

[10] M. N. Nasim, B. Nawaz, S. K. Das, A. SubLaban, L. M. G.-C. González, J. R. Serrano, and J. H. Mack, Manipulating hydrogen oxy-combustion through carbon dioxide addition, Fuel 357 (2024) 129844. DOI: 10.1016/j.fuel.2023.129844.

[11] G. Haixiang, L. Yijing, J. Shang, G. Mingyun, H. Yuanyue, and G. Bing, Learning from class-imbalanced data: Review of methods and applications, Expert Syst. Appl. 73 (2017) 220–239. DOI: 10.1016/j.eswa.2016.12.035.

[12] M. Middlehurst, J. Large, M. Flynn, J. Lines, A. Bostrom, and A. Bagnall, HIVE-COTE 2.0: A New Meta Ensemble for Time Series Classification, Mach. Learn. 110 (2021) 3211–3243. DOI: 10.1007/s10994-021-06057-9.

[13] M. Middlehurst, A. Ismail-Fawaz, A. Guillaume, C. Holder, D. Guijo-Rubio, G. Bulatova, L. Tsaprounis, L. Mentel, M. Walter, P. Schäfer, and A. Bagnall, aeon: a Python Toolkit for Learning from Time Series, Journal of Machine Learning Research 25 (2024) 1–10, URL: http://jmlr.org/papers/v25/23-1444.html.