Tomographic Imaging and Deep Learning based Reconstruction of Burner Flames

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Abstract—This paper presents a tomographic and deep learning (DL) technique for the three-dimensional (3-D) reconstruction of burner flames. Two-dimensional (2-D) flame images are obtained using a tomographic imaging system from different directions around the burner. A flame data augmentation technique using a morphological operator is used to generate the complete training and testing datasets. The simultaneous algebraic reconstruction technique (SART) is used to generate the ground truth, i.e., flame cross-sectional datasets. A DL method based on a convolutional neural network (CNN) is employed for the reconstruction of the flame cross- and longitudinal sections. The CNN parameters are optimized through a trial-and-error approach as well as simulation. The CNN is constructed using a machine learning (ML) hardware accelerator i.e., a tensor processing unit to perform faster reconstruction. The proposed model is evaluated using the 2-D flame images obtained on a lab-scale gas-fired test rig under different operation conditions. Results obtained from the experiments suggest that the proposed strategy can accurately and faster reconstruct the flame cross- and longitudinal sections.

Keywords—flame, tomographic imaging, deep learning, 3-D reconstruction

I. INTRODUCTION

Due to increasingly tighter government regulations, the power generation sector and other industries with energy-intensive processes are required to maximize combustion efficiency and reduce pollutant emissions in their combustion systems (such as boilers and gas turbines). Therefore, combustion monitoring and diagnosis play a vital role in controlling and optimizing such combustion processes [1]. A flame, as the central reaction zone of the combustion process, has a number of characteristic parameters such as size, shape, brightness, uniformity, temperature and oscillation frequency [2]. The monitoring and characterization of these parameters have become increasingly important for an in-depth understanding of the combustion process. With the advances in digital imaging and computing technology, digital imaging-based volumetric tomography (VT) techniques have attracted great attention in combustion research due to their unique features including three-dimensional (3-D) visualization, non-intrusiveness, relatively simple system set-up and easy implementation, making them suitable for the spatial and temporal monitoring and characterization on practical combustion systems [3, 4]. Conventional iterative techniques such as the Algebraic Reconstruction Technique (ART) [5] and the Simultaneous ART (SART) [6] were used successfully in the 3-D reconstruction of flames. However, these techniques have limitations such as high computational cost and offline reconstruction.

In recent years, the 3-D reconstruction of burner flames through Deep Learning (DL) has increasingly attracted the interest of combustion researchers and engineers. It has demonstrated an impressive performance in terms of reconstruction accuracy and computational efficiency compared with the conventional 3-D reconstruction approaches [7, 8, 9]. The widely used DL models are the Convolutional Neural Networks (CNNs) which have been applied in various tomographic applications including ultrasonic, magnetic resonance and X-ray computed tomography (CT) [10-12]. For instance, Ying, et al. [7] developed a CNN-based tomography system using 12 color Charge-Coupled Device (CCD) cameras for rapid 3-D flame chemiluminescence reconstruction. Huang, et al. [8] designed a hybrid model utilizing a CNN and Long Short-Term Memory (LSTM) model for reconstructing 3-D flame structures indirectly from 2-D projections without explicitly tomographic reconstruction. Wang, et al. [9] performed the 3-D reconstruction of turbulent flames based on the CNN and recurrent neural network models. To solve the inversion problem in the CT system, Huang, et al. [13] proposed a CNN and proper orthogonal decomposition (POD) based solution for the flame reconstruction. Cai, et al. [14] show the feasibility of using Transfer Learning (TL) for the VT flame reconstruction, where a CNN is implemented using both the TL and semi-supervised learning techniques. The above-mentioned studies demonstrate that the DL techniques can be used for the 3-D reconstruction of flames with a similar level of accuracy as conventional tomographic techniques. However, whilst the DL approaches have proven promising for 3-D flame reconstruction, they rely on a large amount of experimental data, which can sometimes be challenging to obtain.

In addition, the performance of DL models in real-time measurements or online monitoring of burner flames can be improved by machine learning (ML) hardware accelerators. This provides significant performance, energy efficiency, and cost-effectiveness advantages. Hardware accelerators for ML are specifically designed to handle heavy computational demands. Multiple cores or specialized units enable them to perform parallel computations more efficiently than central processing units (CPUs). Using parallelism, larger datasets and more complex models can be trained and inferred faster. In comparison to CPUs, ML hardware accelerators deliver high performance while using less power. Energy efficiency is especially beneficial when ML workloads are deployed in resource-constrained environments, such as mobile devices or edge computing devices. The use of ML hardware accelerators such as tensor processing units (TPUs) [15] is often more cost-effective than scaling a CPU-based infrastructure. ML hardware accelerators can deliver superior performance at a lower price, making them an appealing option for organizations and researchers. Though various DL-based 3-D flame reconstruction applications have been studied, the majority of these have concentrated on CPU and GPU-based implementations.