

## **BURNERS, COMBUSTION AND HEAT TRANSFER**

### **(663) - (\*) - DEEP LEARNING-BASED SEGMENTATION OF OVERLAPPING FLAMES IN INDUSTRIAL COMBUSTION CHAMBERS**

Markus Vogelbacher (Germany)<sup>1</sup>; Patrick Waibel (Germany)<sup>2</sup>; Julius Großkopf (Germany)<sup>1</sup>; Jörg Matthes (Germany)<sup>1</sup>

1 - Institute for Automation und Applied Informatics, Karlsruher Institute of Technology, Hermann-von-Helmholtz-Platz 1, 76344 Eggensein-Leopoldshafen , Germany; 2 - Kistler Group, Competence Center Vision Systems, 76131 Karlsruhe, Germany

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The monitoring of the burner flame in industrial combustion processes can be supported by the automatic detection and segmentation of the flame in camera images. In addition to the brightness of the flame and thus the temperature, also geometric parameters of the flame can be extracted by a suitable segmentation. With this information, a fluctuating energy input due to unstable flames or even if the flame hits the combustion chamber wall can be detected at an early stage and counteracted. The information obtained from the flame segmentation can also be used for an automatic burner control.

Due to the low contrast and the high variability of the shape and texture of the flame, segmenting the flame is challenging even for a human observer. If there is more than one flame in the camera images, for example in the afterburner chamber of rotary kiln waste incineration plant, overlapping of the flames can make an evaluation even more difficult. Classic segmentation methods from image processing reach their limits in these cases.

In our article, we examine the suitability of various deep learning approaches for flame segmentation in the afterburner chamber of a research plant for special waste incineration. The segmentation quality for different convolutional neural networks is evaluated especially for challenging situations. In addition, the influence of the used image data to the segmentation result is examined. Special attention is paid to the preprocessing of the image data. For example, a temporal low-pass filtering of the camera images can reduce the dynamics of the flame and thus influence the stability of the segmentation result.

The investigation and comparison of the various influencing factors enables a final comparison and conclusion on the suitability of deep learning methods for flame segmentation.

**Palavras-chave : flame monitoring, flame segmentation, deep learning**