Flame analysis using image processing techniques

Albert Chang Her Jie¹, Ahmad Faizal Ahmad Zamli², Ahmad Zulazlan Shah Zulkiffli⁴, Joanne Lim Mun Yee¹ and Mooktzeng Lim²

¹ School of Engineering, Monash University Malaysia.
² Fuels and Combustion, TNB Research Sdn. Bhd., Malaysia.

E-mail: mook.tzeng@tnb.com.my

Abstract. This paper presents image processing techniques with the use of fuzzy logic and neural network approach to perform flame analysis. Flame diagnostic is important in the industry to extract relevant information from flame images. Experiment test is carried out in a model industrial burner with different flow rates. Flame features such as luminous and spectral parameters are extracted using image processing and Fast Fourier Transform (FFT). Flame images are acquired using FLIR infrared camera. Non-linearities such as thermal acoustic oscillations and background noise affect the stability of flame. Flame velocity is one of the important characteristics that determines stability of flame. In this paper, an image processing method is proposed to determine flame velocity. Power spectral density (PSD) graph is a good tool for vibration analysis where flame stability can be approximated. However, a more intelligent diagnostic system is needed to automatically determine flame stability. In this paper, flame features of different flow rates are compared and analyzed. The selected flame features are used as inputs to the proposed fuzzy inference system to determine flame stability. Neural network is used to test the performance of the fuzzy inference system.

1. Introduction
Flame visualization and characterization using digital image processing is a tool to provide an understanding of flame features related to flame stability. Flame features are extracted in both time and frequency domains of flame with different flow rates to perform flame analysis. The features in time domain are the luminous parameters, while features in frequency domain are the spectral parameters. Flame velocity determines the rate of expansion of flame, while thermal acoustic oscillations cause wear and tear to burners in industry, thus affecting flame stability. Unstable flames also cause harmful effects such as release of nitrogen oxide gas, thermal stress and vibrational phenomena [1].

The flame images’ brightness is used to approximate flame velocity [2], while flame visualization and characterization techniques extract luminous and spectral parameters that represents combustion states for monitoring and control purposes [3, 4]. Fuel (or coal) type can be identified through image processing of its flame features under various combustion conditions [5]. Features extracted using digital signal processing are used as inputs to fuzzy inference system for identification of coal type being burnt [6]. Neural networks are used to map flame features to fuel type [7], while power spectral densities (PSD) have been used to provide oscillatory characteristics of flames, which is important to understand the flame structure and stability [8]. Other parameter such as the oscillation frequency has been obtained from image processing to derive a universal index, a simple universal index for flame stability assessment [9].
The above flame visualization methods have been carried out using advanced optical cameras, and are more suitable for laboratory research studies. A more simpler and cost-effective method is required to capture flame images in industrial furnaces. Infrared (IR) cameras are suitable to capture flame images as it is able to capture the flame radiation and movement of flame [2]. Flame images are processed using image processing techniques with Fast Fourier Transform (FFT) to extract flame features.

The main contributions of this work are as follows. First, the mean velocities of the flames for different fuel flow rates are determined using the image processing techniques. The PSD of the flame with different flow rates are then determined for comparison. The second contribution of the work includes a fuzzy logic scheme which uses the extracted luminous features as inputs to predict flame stability. Finally, a neural network approach is used to investigate the performance of the fuzzy inference system and the correlation between the flame features with the flame stability.

2. Methodology

2.1. Combustion Test Facility and Experiments
Flame images are recorded from a lab scale burner in TNB Research Sdn. Bhd. that has a diameter of 50mm as shown in Figure 1. Two videos are recorded for flames with different fuel flow rates of 15 lpm CO2 + 10 lpm CH4 flow rate and 30 lpm CO2 + 10 lpm CH4. The videos are recorded using an IR camera from FLIR (model A615). The videos are used to extract a sequence of images for image processing.

![Figure 1. Lab scale (and diameter) of burner at TNB Research Sdn. Bhd.](image)

2.2. Measurement principles

2.2.1. Image processing. The images are first pre-processed to segment the central area of flame and the background noise are filtered. The techniques used are image thresholding, color space transformation and edge detection. The techniques are discussed further in the following sections:

(i) **Image Thresholding.** Otsu’s thresholding method is used to select a threshold value of \(k\) by computing probabilities of bright and dark pixels based on the histogram. The background noise is separated from the flame central area based on the threshold \(k\) value (refer Figure 2) [10].

(ii) **Color space transformation from RGB to HSV.** The hue, saturation, value (HSV) of the images are known to have a better correlation with the optical emission spectra and the flame temperature. This is because the color intensity (as it varies with the flame intensity or brightness) is separately stored in the value component. Thus the RGB images (after the
threshold has been applied) are transformed to HSV images for further processing (refer Figure 3).

(iii) **Edge detection using Sobel filter.** Edges of the flame images represent its’ shape and structure and therefore needs to be identified as accurate as possible [12]. In this study, a filtering method by Sobel is used to determine the edges of the flame by applying convolving masks to the image in the x and y directions (refer Figure 4).

### 2.2.2. Proposed method to determine flame velocity

The area of the flame is filled with white pixels after edge detection is shown in Figure 5. The images are then converted back to grayscale image as shown in Figure 5. A threshold value is applied to the grayscale images based on equation (1). A white pixel is detected if the grayscale value is greater than 1. The mean flame velocity is then approximated by determining the difference in the number of white pixels of the two consecutive image frames, divided by the frame rate of the video as shown in equation (2). The difference in the number of pixels is converted into distance. In this study, 325 pixels represents 50 mm, which is the diameter of the lab scale burner.

\[
\text{no. of white pixels}_f = \sum_{i=0}^{\text{row}-1} \sum_{j=0}^{\text{column}-1} \begin{cases} 
1, & l_f(i,j) > 1 \\
0, & l_f(i,j) < 0
\end{cases}
\]

\[
V_f = \frac{\text{no. of white pixels}_{f+1} - \text{no. of white pixels}_f}{\text{Frame rate of video}}
\]

### 2.2.3 Extraction of flame features

In this study, flame features are divided into luminous parameters and spectral parameters. Luminous parameters such as brightness and its fluctuation provide information on the statistical distribution of the flame’s radiation. Spectral parameters such as power spectral density (PSD) are representative of the flame radiation signals’ distribution and are related to the flame’s stability.

(i) **Luminous parameters.** Each individual pixel of the images represents the grey values in the time domain and is used to determine the brightness and fluctuation. The brightness is determined from equation (3):

\[
x = \frac{1}{N} \sum_{i=1}^{N} x_i \cdot \frac{100}{G}
\]

where \(x_i\) are grey values, \(N\) is the number of values and \(G\) is the maximum gray value.

The fluctuation is determined from equation (4):

\[
\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - x)^2}
\]

The flame area, \(A_i\) is calculated through:

\[
A_i = \frac{1}{\text{Width} \times \text{Height}} \sum_{i=0}^{\text{width}-1} \sum_{j=0}^{\text{height}-1} \begin{cases} 
1, & I_i(i,j) > \text{threshold} \\
0, & \text{other}
\end{cases}
\]

where the threshold is estimated from the maximum background noise of the image [9]. Previous work has shown that the brightness of the image is related to radiation level while
the fluctuation is related to non-uniformity of the flame [3]. Thus the flame area indicates the distribution of flame’s energy content to the surrounding space.

(ii) Spectral parameters. Spectral parameters are frequency domain features, and is an analysis of natural resonance. Spectral parameters are used to monitor vibration signals and ball bearing faults [13]. This study uses power spectral densities (PSD) to determine the fluctuation of the flame. The PSD is given as:

$$ P_k(f) = \frac{1}{N} (X_N(f))^2 $$

(6)

where $P_f$ is the PSD estimate, $N$ is the number of samples and $X_N(f)$ is obtained via Fast Fourier Transform (FFT) of the $N$ data sequence. Based on the PSD, the flame’s flicker $F$ (or the flame’s fluctuation) is given as:

$$ F = \frac{\sum_{k=1}^{N-1} P_k \cdot f_k}{\sum_{k=0}^{N-1} P_k} $$

(7)

where $P_k$ is the PSD of kth frequency and $f_k$ is the kth frequency.

**Figure 2.** (left) snapshot of the flame from the IR camera videos (right) RGB image after Otsu’s thresholding.

**Figure 3.** (Comparison of RGB and HSV components of flame image.)
3. Results and discussions

In this section, the mean velocities and PSD of the flame with different flow rates are compared and analyzed. A discussion of the flame features from the proposed fuzzy inference system is presented.

3.1. Mean velocity and PSD of flame with different flow rates

3.1.1 Mean velocities. The flame velocities with respect to time for 15 and 30 lpm CO$_2$ are shown in Figure 6, while Table 1 shows the mean flame velocities and the standard deviations for both flames. From Table 1, the results show that there is no significant difference in mean velocities and standard deviation for both flames with different CO$_2$ flow rates. This is because in both cases the flames are opened or exposed to the surroundings, and the amount of oxidant are not in a controlled environment.

3.1.2 Power spectral densities. The PSD of both flames (obtained from FFT) are shown in Figure 7. The histograms for the PSD are shown in Figure 8. Based on the histogram plot in Figure 8, it can be observed that with a higher CO$_2$ flow rate (30 lpm), there are higher occurrences of oscillations. The dominant PSD range is also higher at 0.8 to 1.0 (refer Table 1). The flame is also observed to be more turbulent. This is because the flame with a higher flow rate (30 lpm) is more affected by non-linearities such as thermal oscillations.
Figure 6. (Graph of mean velocities of 15lpm flame (left) and 30lpm (right)).

Table 1. Mean velocity and standard deviation of flame with different CO$_2$ flow rates and 10 lpm CH$_4$.

| Flow rate       | 15 lpm CO$_2$ + 10 lpm CH$_4$ | 30 lpm CO$_2$ + 10 lpm CH$_4$ |
|-----------------|-------------------------------|-------------------------------|
| Mean velocity (m/s) | 0.4120                        | 0.4074                        |
| Standard deviation (m/s) | 0.0694                        | 0.0607                        |
| PSD             | 0.6-0.8                       | 0.8-1.0                       |

Figure 7. Power spectral density vs Frequency of flame for 15lpm (left) and 30lpm (right).

Figure 8. Histogram of PSD of flame for 15lpm (left) and 30lpm (right).
3.2. Features Extraction

The flame features are extracted as inputs to the proposed fuzzy inference system. The extracted features in terms of the brightness, fluctuation amplitude, flame area and flicker are shown in Figure 9 to 11. The mean values of the extracted features are then shown in Table 2.

3.2.1 Brightness. Based on Table 2, the mean brightness of the flame with 30 lpm CO$_2$ + 10 lpm CH$_4$ flow rates is lower than the flame with 15 lpm CO$_2$ + 10 lpm CH$_4$. This is caused by the higher CO$_2$ flow rate. Both flames have a constant CH$_4$ flow rate at 10 lpm and are mixed with CO$_2$ before it is ignited at the outlet of the burner. At a higher CO$_2$ flow rate, the total energy content in the gas that comes from CH$_4$ is diluted. Hence, the flame with a higher CO$_2$ flow rate is not as intense nor bright. The fluctuation amplitude and flicker for flame with 15 lpm CO$_2$ + 10 lpm CH$_4$ is higher because it has a higher energy content compared to the flame with 30 lpm CO$_2$ + 10 lpm CH$_4$. The change in the fluctuation amplitude represents a change in the luminous radiation, while the change in flicker reflects a change in the flame geometry. Unlike the mean flame velocities which are similar, these flame features show that both flames are distinctly different.

![Figure 9. Mean brightness of flame for 15 lpm (left) and 30 lpm (right).](image)

![Figure 10. Fluctuation amplitude of flame for 15 lpm (left) and 30 lpm (right).](image)
Figure 11. Flame area and flicker for CO\textsubscript{2} flow rates of 15 and 30 lpm.

Table 2. Mean brightness, fluctuation and area of flame with different flow rates.

| Flow rate | 15 lpm CO\textsubscript{2} + 10 lpm CH\textsubscript{4} | 30 lpm CO\textsubscript{2} + 10 lpm CH\textsubscript{4} |
|-----------|----------------------|----------------------|
| Mean Brightness | 0.16         | 0.12         |
| Mean Fluctuation  | 3.48         | 2.95         |
| Mean Area       | 0.1855       | 0.2055       |

3.3. Implementation and Evaluation of fuzzy inference system

The brightness, fluctuation and flame area are used as inputs for the fuzzy inference system. The membership function for each input is shown from Figures 12 to 13. The performance of the fuzzy inference system is evaluated using a neural network fitting function by plotting the regression and mean square error as shown in Figures 13 and 14.

Figure 12. Membership function for (top left) brightness, (top right) fluctuations, and flicker (bottom) area.
Based on Figure 13, the regression for the 15 lpm CO\textsubscript{2} is 0.58 while the regression for 30 lpm flame is 0.97. The significant difference in the values is due to greater number of samples obtained for the flame with 30 lpm CO\textsubscript{2} taken from the neural network. The video recorded for the 30 lpm CO\textsubscript{2} flame was longer (31s) compared to the 15 lpm CO\textsubscript{2} flame (24s). The high regression value for the 30 lpm CO\textsubscript{2} flame shows that the fuzzy inference system has the potential to simplify the non-linear model into a linear model. Furthermore, it shows the potential to derive linear equations using flame features. The low mean square error shown in Figure 14 shows that the fuzzy inference system is reliable in predicting flame stability.

4. Conclusions

An image processing technique is proposed to determine the flame velocities flame for different fuel flow rates. No significant difference in flame velocities is observed for flames with CO\textsubscript{2} flow rates of 15 lpm and 30 lpm. The higher oscillation in flame with flow rate of 30 lpm CO\textsubscript{2} shows that the flame with flow rate of 15 lpm CO\textsubscript{2} is more stable. In addition, flame features such as brightness, fluctuation and flicker show that flame with CO\textsubscript{2} flow rates of 15 and 30 lpm are distinctly different. A proposed fuzzy inference system using extracted features as input to predict flame stability produces good performance from neural network but more experiments are needed to validate the results.
Acknowledgement
The authors would like to thank TNB Research Sdn. Bhd. for providing the facility and the data needed for the experiment.

References
[1] Y. Ren, S. Li, W. Cui, Y. Zhang, and L. Ma, "Low-frequency AC electric field induced thermoacoustic oscillation of a premixed stagnation flame," Combustion and Flame, vol. 176, pp. 479-488, 2017.
[2] Mook Tzeng Lim, Ahmad Rashidi, Soong Der Chen, Noor Akma Watie Mohd Noor, Azmi Ahmad, Hamdan Hassan, et al., "Preliminary determination of flame velocities fro infrared images using image processing techniques in a 150 kWth coal-fired combustion test rig," Advances in Mechanical, Aeronautical and Production Techniques (MAPT), pp. 1-5, 2015.
[3] A. González-Cencerrado, B. Peña, and A. Gil, "Coal flame characterization by means of digital image processing in a semi-industrial scale PF swirl burner," Applied energy, vol. 94, pp. 375-384, 2012.
[4] R. Hernandez and J. Ballester, "Flame imaging as a diagnostic tool for industrial combustion," Combustion and flame, vol. 155, pp. 509-528, 2008.
[5] H. Zhou, Q. Tang, L. Yang, Y. Yan, G. Lu, and K. Cen, "Support vector machine based online coal identification through advanced flame monitoring," Fuel, vol. 117, pp. 944-951, 2014.
[6] L. Xu, Y. Yan, S. Cornwell, and G. Riley, "On-line fuel identification using digital signal processing and fuzzy inference techniques," IEEE Transactions on Instrumentation and Measurement, vol. 53, pp. 1316-1320, 2004.
[7] L. Xu, Y. Yan, S. Cornwell, and G. Riley, "Online fuel tracking by combining principal component analysis and neural network techniques," IEEE Transactions on Instrumentation and Measurement, vol. 54, pp. 1640-1645, 2005.
[8] G. Lu, Y. Yan, M. Colechin, and R. Hill, "Monitoring of oscillatory characteristics of pulverized coal flames through image processing and spectral analysis," IEEE transactions on instrumentation and measurement, vol. 55, pp. 226-231, 2006.
[9] D. Sun, G. Lu, H. Zhou, Y. Yan, and S. Liu, "Quantitative assessment of flame stability through image processing and spectral analysis," IEEE Transactions on Instrumentation and Measurement, vol. 64, pp. 3323-3333, 2015.
[10] N. Otsu, "A threshold selection method from gray-level histograms," Automatica, vol. 11, pp. 23-27, 1975.
[11] W.-B. Horng, J.-W. Peng, and C.-Y. Chen, "A new image-based real-time flame detection method using color analysis," in Networking, Sensing and Control, 2005. Proceedings. 2005 IEEE, pp. 100-105.
[12] T. Qiu, Y. Yan, and G. Lu, "An Autoadaptive Edge-Detection Algorithm for Flame and Fire Image Processing," IEEE Transactions on Instrumentation and Measurement, vol. 61, pp. 1486-1493, 2012.
[13] I. Attoui, N. Fergani, N. Boutasseta, B. Oudjani, and A. Deliou, "A new time–frequency method for identification and classification of ball bearing faults," Journal of Sound and Vibration, vol. 397, pp. 241-265, 2017.