Indian Journal of Science and Technology, Vol 9(6), DOI: 10.17485/ijst/2016/v9i6/79904, February 2016 ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Comparative Analysis of Flame Image Features for Combustion Analysis

Abi P. Mathew[1*], A. Asokan[2], K. Batri[3] and D. Sivakumar[2]

[1]St. Joseph's College of Engineering and Technology, Palai, Bharananganam Pravithanam Road, Choondacherry – 686579, Kerala, India; abimthw@gmail.com
[2]Department of Instrumentation, Annamalai University, Rukmani Lakshmipathy Road, Egmore, Chennai – 600008, Tamil Nadu, India; asokan2k7@gmail.com, dsk2k5@gmail.com
[3]PSNA College of Engineering and Technology, Kothandaraman Nagar, National Highway 209, Dindigul – 624622, Tamil Nadu, India; krishnan.batri@gmail.com

Abstract

Background/ Objective: This article identifies the best feature of the flame video, captured with a camera with frequency response in visible spectrum, from which the flame temperature can be estimated. **Methods/Statistical analysis:** The flame videos at different air and fuel inlets with different boiler temperatures were recorded from a diesel fired boiler prototype. In the video frames, the flame region was localised by intensity based adaptive thresholding. The correlation between boiler temperature and measures of central tendency and dispersion of different colour channels of the video frames were investigated. **Findings:** Among the features of the flame video, Standard deviation of blue channel grey levels above 32.95, variance greater than 1293 and mean absolute deviation (MAD) above 30.38 could efficiently represent the region of optimum combustion air supply at which boiler temperature is maximum above 684 degree Celsius. Range of green channel grey levels, interquartile mean, variance and mean absolute deviation of blue channel grey levels are the video features exhibiting maximum correlation (ρ>-0.96) with boiler temperature. **Applications/Improvements:** The features of the flame video which are correlated with its temperature can be utilised to develop non-intrusive methods of temperature measurement. This will enable efficient control of combustion process.

Keywords: Combustion, Flame Image Processing, Flame Temperature Measurement, Image Features, Video Processing

1. Introduction

Combustion monitoring and control has been vital in industrial boilers. Monitoring combustion process has always been an area of fascination for researchers over the decades. Image processing has been the tool for analysis of the flame in most of the non-intrusive approachees[1-12]. An attempt to study combustion process for different fuels through analysis of flame image is made by[1]. 3-D reconstruction and visualization of the flame structure are done using images captured from multiple directions in many of the studies[2-5]. In[3] proposed a multi-camera based imaging system for 3-D visualization and characterisation of the flame front structures of a turbulent gaseous flame.

3-D temperature profiling and visualization[4,5] is an advancement of the mere reconstruction of the 3-D flame structure. In[6] development of image based online monitoring and characterisation of fossil fuel fired flames is detailed. In[7] the temperature profile and emissivity images are derived from a colour image. Temperature estimation and distribution in the flame field is detailed in[8]. Flame images taken by high dynamic range cameras processed for reconstructing the flame radiance existence field is detailed in[9]. It is challenging to identify the video features through which the flame temperature can be measured or to identify the range of these features corresponding to optimum combustion. Using a commercially available video camera of visible spectrum, the task is challenging than using an IR camera. Analysis of combustion from

*Author for correspondence

video using IR camera had been done by[10]. In[11] a radiation model was developed to relate the flame images with the 2-D temperature distribution. It is worthy if a relation between boiler temperature and features extracted from the flame video, captured with a camera of visible spectrum can be established.

The objective of most of the literature had been analysis of combustion status using features extracted from the flame image or video without taking the combustion parameters into account. Combustion parameters like air inlet flow rate and fuel flow rate has predominant influence on boiler temperature and combustion status. Through this experimental research, an attempt has been made to analyse the features of flame systematically at regular intervals of inlet air variations and thereby at different boiler temperatures. The regular variation of inlet air flow in turn generates distinct flame structures and intensity features. The investigation is to identify the video features which are correlated to the boiler flame temperature and the range of these features which characterise the optimum combustion.

2. Experimental Configuration

The experiment comprises capturing video of turbulent boiler flame, at known combustion conditions and boiler temperature for extracting video features. Experiments are done in a diesel fired, coil type fully automatic-instant steam generating boiler[12] which is shown in Figure 1. Inlet air supply to the boiler is supplied by a forced draft (FD) fan rotating at 1480 rpm with inlet opening controlled by an adjustable damper. The diesel pressure at the outlet of fuel injection pump is maintained constant at 12.5kg/cm^2 during the video acquisition. At this constant diesel supply, the amount of combustion air into the boiler is varied gradually by changing the percentage opening of the damper. Simultaneously video of the diesel flame is captured. To correlate the flame video features directly to the boiler temperature, instead of steam temperature, a K-type thermocouple is inserted into the boiler to measure the flame temperature. Video of flame is captured at a frame rate of 30 frames per second by a CCD camera through the sight glass of boiler. By maintaining the amount of combustion air at different levels, the boiler temperature is noted and corresponding video is captured for five seconds each.

Figure 1. Diesel fired boiler prototype.

Each video segment corresponding to a particular level of combustion air comprises approximately one hundred and fifty frames. Features from each frame are extracted and cumulative feature of the video segment is estimated from the median, arithmetic mean and quadratic mean of individual frame features, to eliminate influence of outliers. Schematic of experimental setup is given in Figure 2. The figure explains the inlet parameters as air inlet and fuel inlet for combustion and a CCD camera is utilised for capturing video signals. The temperature measured is fed to the computing system for further processing.

3. Segmentation of Local Flame Region

Instead of the global frame features, local features of the flame region are extracted. The flame region has been segmented from red, green and blue channels of whole

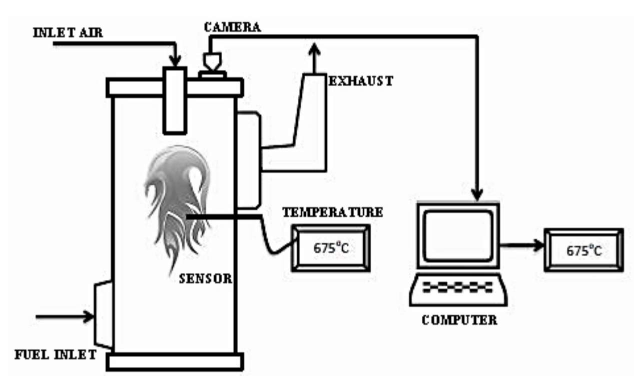

Figure 2. Experimental Configuration.

frames, by masking these channels with a multiplication mask. This is possible as the grey level intensities at the flame region is higher than the other image regions. The binary multiplication mask is generated by thresholding the greyscale image obtained from the RGB frame. In fact, the intensity features of each frame are unique and different hence a constant threshold may not be applicable to the entire frames in the video segment. To determine the optimum threshold suitable for each frame, Otsu's method[13] is employed. The multiplication mask to isolate R, G and B channel grey levels in the local flame region is generated by thresholding the grey scale version of the video frame using the optimal Otsu's threshold. The mathematical strategy adopted for estimating optimum threshold is as,

Let L is the maximum possible grey level in the grey-scale version of the video frame. The normalised grey level histogram of grey scale video frame,

$$P_i = n_i/N \quad P_i \geq 0, \quad \sum_{i=1}^{L} P_i = 1 \tag{1}$$

where N is the total number of pixels in the greyscale frame, ni is the number of occurrence of grey level 'i' and pi is its discrete probability density, given, i = { 0,1,2,… ..L}. If the grey levels are assumed to be of two classes C0 and C1, separated by a threshold, 'k', so that,

C0 = {0, 1, 2 … k} and C1 = {k + 1…..L}. This means that the intensities present in the greyscale video frame belongs to two classes or regions, local flame region and non-flame region. Then the probabilities of class occurrence and the class mean levels, respectively, are given by,

$$\omega_0 = \Pr(C_0) = \sum_{i=1}^{K} P_i = \omega(k) \tag{2}$$

$$\omega_1 = \Pr(C_1) = \sum_{i=k+1}^{L} P_i = 1 - \omega(k) \tag{3}$$

$$\mu_0 = \sum_{i=1}^{k} i \Pr(i/C_0) = \sum_{i=1}^{k} iP_i/\omega_0 = \mu(k)/\omega(k) \tag{4}$$

$$\mu_1 = \sum_{i=k+1}^{L} i \Pr(i/C_0) = \sum_{i=k+1}^{L} ip_i/\omega_1 = \frac{\mu_T - \mu(k)}{1 - \omega(k)} \tag{5}$$

$$\omega(k) = \sum_{i=1}^{k} Pi \tag{6}$$

$$\mu(k) = \sum_{i=1}^{k} ip_i \tag{7}$$

Where ω(k) and μ(k) are the zeroth and first order cumulative moments of the histogram up to the kth level, respectively.

$$\mu_T = \mu(L) = \sum_{i=1}^{L} ip_i \tag{8}$$

μ_T is the mean of the grey levels in the grey scale version of R,G, B video frame.

$$\omega_0\mu_0 + \omega_1\mu_1 = \mu_T, \quad \omega_0 + \omega_1 = 1, \quad k \tag{9}$$

The variances of intensities in the flame and non-flame regions respectively are given by,

$$\sigma_0^2 = \sum_{i=1}^{k} (i - \mu_0)^2 \ \Pr(i/C_0) = \sum_{i=1}^{k} (i - \mu_0)^2 \ P_i/\omega_0 \tag{10}$$

$$\sigma_1^2 = \sum_{i=k+1}^{L} (i - \mu_1)^2 \Pr(i/C_1) = \sum_{i=k+1}^{k} (i - \mu_1)^2 \ P_i/\omega_1 \tag{11}$$

To evaluate the performance of the threshold 'k', in differentiating the flame and non-flame regions in the greyscale frame, following discriminant criterion is used,

$$\lambda = \sigma_B^2/\sigma_W^2 \quad K = \sigma_T^2/\sigma_W^2 \quad \eta = \sigma_B^2/\sigma_W^2 \tag{12}$$

where

$$\sigma_W^2 = \omega_0\sigma_0^2 + \omega_1\sigma_1^2 \tag{13}$$

$$\sigma_B^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 = \omega_0\omega_1(\mu_1 - \mu_0)^2 \tag{14}$$

from (9)

$$\sigma_T^2 = \sum_{i=1}^{L} (i - \mu_T)^2 P_i \tag{15}$$

where λ, K and η are within class variance, between class variance, and variance of total grey levels. At optimum threshold k, the object function (12) maximizes

The discriminant criteria maximizing λ, K, η respectively, for k are, however, equivalent to one another; *e.g.*, K = λ + 1 and η = λ/(λ + 1) in terms of λ, because the following basic relation always holds:

$$\sigma_W^2 + \sigma_B^2 = \sigma_T^2 \tag{16}$$

It is noticed that σ_w^2 and σ_B^2 are functions of threshold level k, but σ_T^2 is independent of k. It is also noted that σ_w^2

is based on the second order statistics while σ_B^2 is based on the first order statistics. Therefore, η is the simplest measure with respect to k. Thus at the optimum threshold 'k', the object function η maximises.

The optimal threshold 'k' which maximises η or equivalently maximises σ_B^2, is selected through a sequential search using (6) and (7), or explicitly using (2)–(5):

$$\sigma_B^2(k) = \frac{[\mu_T \omega_{(k)-} \mu(k)]^2}{\omega_{(k)}[1-\omega(k)]} \tag{17}$$

and the optimal threshold k^* which separates the flame and non-flame regions in the greyscale video frame is

$$\sigma_B^2(k^*) = \max_{1 \le k < L} \sigma_B^2(k) \tag{18}$$

The multiplication mask used to extract R G and B channel grey levels in the local flame region,

$$\hat{f}(i,j) = \begin{cases} 1 & \text{if} \quad f(i,j) \ge k \\ 0 & \text{else} \end{cases} \tag{19}$$

Where f(i, j) is the grey scale version of the video frame.

$$\begin{vmatrix} \hat{R}(i,j) \\ \hat{G}(i,j) \\ \hat{B}(i,j) \end{vmatrix} = \begin{vmatrix} R(i,j) \\ G(i,j) \\ B(i,j) \end{vmatrix} * \hat{f}(i,j) \tag{20}$$

$\hat{R}(i\ j)$, $\hat{G}(i,j)$ and $\hat{B}(i,j)$ are the grey levels of the R, G and B channels in the local flame region.

The original RGB video frame, its grey scale version, the binary multiplication mask generated and the segmented flame region is demonstrated in Figure 3 to Figure 6 consecutively.

Figure 3. RGB video frame.

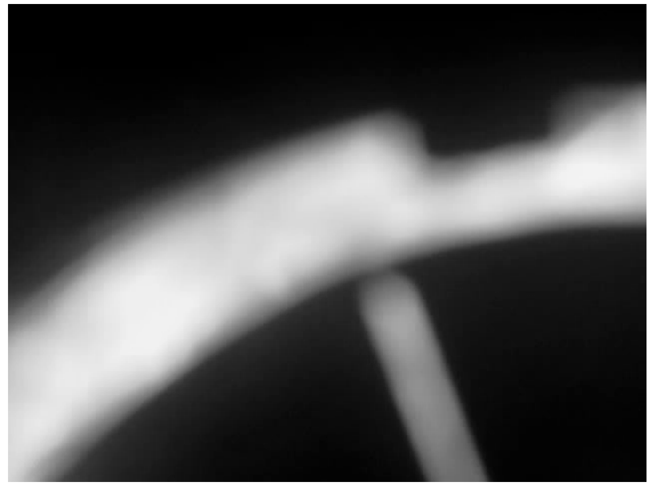

Figure 4. Grey scale version of Figure 3.

Figure 5. Multiplication mask.

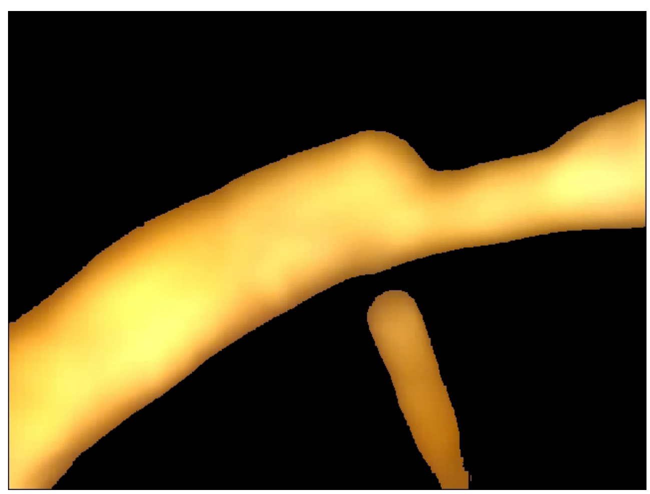

Figure 6. Segmented flame region.

Segmentation of flame region from the video frame, extraction of local flame features and the analysis of the dependency of video features on the combustion air supply and boiler temperature are performed in Matlab.

4. Extraction of Features from Flame Video

The video has been captured at various levels of combustion and boiler temperature by continuously varying the combustion air flow. The flame region is extracted from the video frame. Intensity features and histogram features of the local flame region of each frame is computed. As mentioned earlier features from individual frames in each video segment is extracted. Features of individual frames in a video segment are integrated to reflect the features of the video segment. The term 'video segment' refers to the flame video captured for a particular value of boiler temperature and combustion air flow.

Spread is a geometrical feature extracted from the frame, which represent the area of the flame. The 'spread' of the flame in each frame is computed by counting the number of '1's in the corresponding binary multiplication mask. The wavelength of the spectral emissions of the flame changes with respect to the temperature. Hence, the intensity or histogram features can better reflect the combustion efficiency rather than textural or geometrical features. The intensity features extracted from the video frames are the measures of dispersion and central tendency of grey levels in R, G, and B channels of the segmented flame region. These measures of central tendency and dispersion computed are mode of local intensity, arithmetic mean, quadratic mean, root mean square intensity, median, geometric mean, variance, standard deviation, MAD, range, IQR and interquartile mean (IQM). The histogram features extracted are skewness and kurtosis.

The median and trimmed mean are robust statistics but arithmetic mean, geometric mean and harmonic mean are not resistant to outliers. Geometric mean and harmonic mean are useful, when the sample is distributed log-normal. The underlying distribution of local-flame intensity in the video frame remains unknown and perhaps, the distribution may be different for individual frames as the flame is turbulent. The probability density function of the variation of local flame features with respect to the index of the frames in a video segment corresponding to certain air-flow rate obviously may not be normally distributed. The probability of interference of outliers is high because of the nonlinear behaviour of the turbulent diesel flame and inherent design aspects of diesel fired boiler. If the sample distribution is normal one, the arithmetic mean may be optimal i.e. minimum variance unbiased estimator. The presence of outlier displaces the average away from the centre of the rest of the data by an arbitrarily large distance. A small fraction of anomalous measurements, with abnormally large deviation from the centre may change the mean of the population substantially. The trimmed mean is a family of measures of central tendency like arithmetic mean and it is a robust statistics. Trimmed or truncated mean is the mean of the population discarding given parts of the probability distribution or sample at the high or low end, typically five percentage, ten percentage or twenty-five percentage based on the sample size. Twenty-five percentage trimmed mean is known as inter quartile mean. Median can be regarded as a fully truncated mean which is most robust. Trimmed mean is suitable for mixed distributions and heavy tailed distributions like Cauchy distribution.

Among the popular measures of dispersion, the standard deviation and variance are optimal minimum variance unbiased estimator for normally distributed data. These are heavily sensitive to outliers whereas MAD, to a certain extent is immune to outliers. IQR is another measure of dispersion which is robust to outliers and suitable for unknown probability distributions. The mode of local flame intensity is the most frequent value or the value exhibiting maximum probability density. When there are multiple intensities with equal incidence, the mode returns the smallest of these intensities. Root mean square or quadratic mean is a measure of central tendency most suitable for a varying quantity especially when the variations are sinusoids. Skewness is a histogram feature that may oscillate between positive and negative values based on whether the local flame intensity histogram of RGB channels are right tailed or left tailed. Skewness is the third moment of dispersion and expresses the lop-sidedness or symmetry of probability density function or intensity histogram. Kurtosis is the fourth moment of dispersion and it is a measure of 'peakedness' of the probability density function of R, G and B channel grey levels in the segmented flame region. Range, which is another measure of dispersion, is the difference between minimum and maximum of the samples and it is prone to outliers. The most robust measure of dispersion, IQR otherwise called mid-spread or middle-fifty is the difference between upper and lower quartiles of the R, G and B channel grey levels, in the segmented flame region.

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|x_i - \mu| \tag{21}$$

$$IQM = \frac{2}{n}\sum_{i=\frac{n}{4}+1}^{\frac{3}{4}n} x_i \tag{22}$$

$$IQR = (Q_3 - Q_2) \tag{23}$$

Where Q3 is the third Quartile and Q2 is the second Quartile

$$\text{Geometric Mean } m_1 = \left[\prod_{i=1}^{n} x_i\right]^{\frac{1}{n}} \tag{24}$$

$$\text{Harmonic Mean } m_2 = \frac{n}{\sum_{i=1}^{n}\frac{1}{x_i}} \tag{25}$$

$$\text{Quadratic Mean } m_3 = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i)^2} \tag{26}$$

Where Arithmetic Mean $\mu = \frac{1}{n}\sum_{i=1}^{n} x_i, x_i$ is the grey levels of R, G and B channels in the segmented flame region of video frame, i = {1, 2, ….. n} where n is the total number of pixels in the segmented local flame region

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2} \tag{27}$$

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2 \tag{28}$$

Median = x_n of a sorted set wof samples x ={x_1, x_2, x_3 …x_{2n}}

The number of pixels getting distributed to different grey level bins of the R, G and B channels changes in response to the variation in furnace temperature. This changes the symmetry and peakedness of histogram.

The skewness is given by,

$$\beta_1 = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^3}{\left[\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2}\right]^3} \tag{29}$$

The kurtosis is given by,

$$\beta_2 = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^4}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2\right]^2} \tag{30}$$

To identify the best of statistical video features which are robust to outliers and can characterise the efficiency of combustion, Pearson correlation coefficient between the video features and the boiler temperature is estimated. The Pearson correlation coefficient (ρ) between boiler temperature and video features is given by

$$\rho = \frac{\sum_{i=1}^{n}(x_i - \mu)(y_i - \mu)}{n\sigma_x\sigma_y} \tag{31}$$

Where x series is the samples of boiler temperature and y series is samples of video segment features. The ranges of these features corresponding to the optimum combustion are also estimated.

5. Experimental Results

As apparent in Figure 19 and Table 1 with the increase in combustion air flow, following a transient shoot-up, a gradual decay of boiler temperature is observed. A comparative evaluation of the relation between features of R, G and B channel grey levels and boiler temperature has been performed. The blue channel grey-level variations exhibit comparatively close relation to the combustion efficiency, as obvious in Figure 7 to Figure 18. The maximum of blue channel grey levels and the mean of blue channel grey-levels fall abruptly with increase in temperature as visible in Figure 7.

This fall in the average and maximum blue channel energy may be in accordance with the increase in IR spectral emission. It has been observed that the features vary significantly among different frames of the same video segment. Perhaps these significant variations may be a reflection of turbulent nature of the flame. Due to this turbulent nature of the flame, some of the frames may have features far from majority of the frames in the same video segment.

The quadratic mean, median and arithmetic mean ‘integrate’ the features of individual frames to form the cumulative feature of video segment. The robust statistics, quadratic mean and median eliminate the probable

Table 1. Range of video segment features and corresponding temperature.

Video Segment feature	Range of the feature	Range of boiler temperature
Mean intensity of blue channel	77.76<	>660
Geometric mean of blue channel	68.19<	>660
Harmonic mean of blue channel	57.95<	>660
Quadratic mean of blue channel	84.76<	>660
Median of blue channel	77 <	>660
Mode of red channel	=255	>647
Mode of blue channel	78<	>660
Minimum intensity of green channel	88<	>660
Minimum intensity of blue channel	8<	>660
Maximum Intensity of blue channel	168<	>650
Range of green channel	>163	>660
Range of blue channel	157<	>647
Interquartile range of blue channel	60<	>660
Standard deviation of blue channel	32.95<	>684
Variance of blue channel	1293<	>684
Mean absolute deviation of blue channel	30.38<	>684

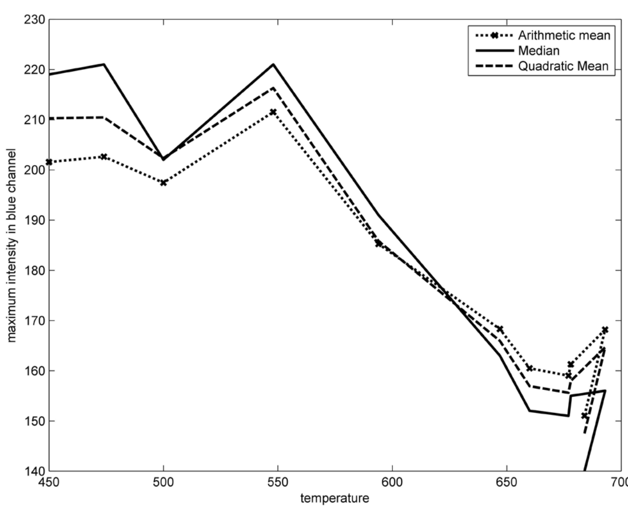

Figure 7. Maximum intensity in blue channel grey levels versus boiler temperature.

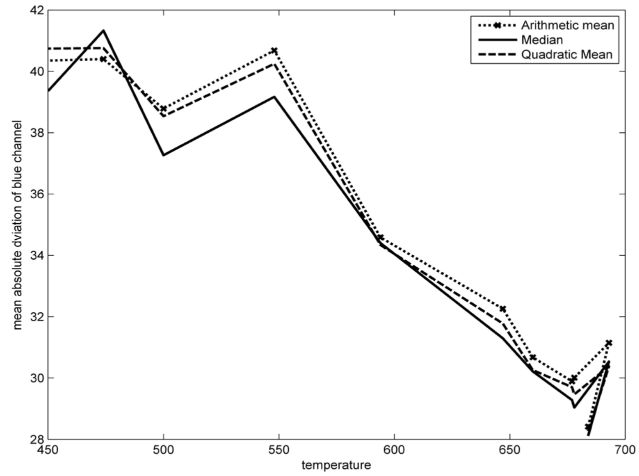

Figure 8. Mean Absolute deviation of blue channel grey levels versus boiler temperature.

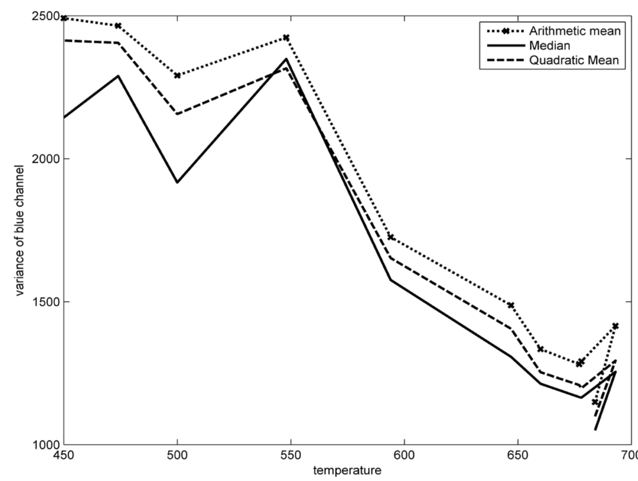

Figure 9. Variance of blue channel grey levels versus boiler temperature.

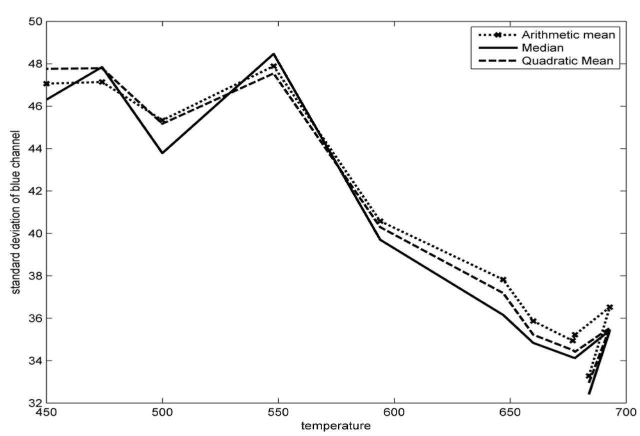

Figure 10. Standard deviation of blue channel grey levels versus boiler temperature.

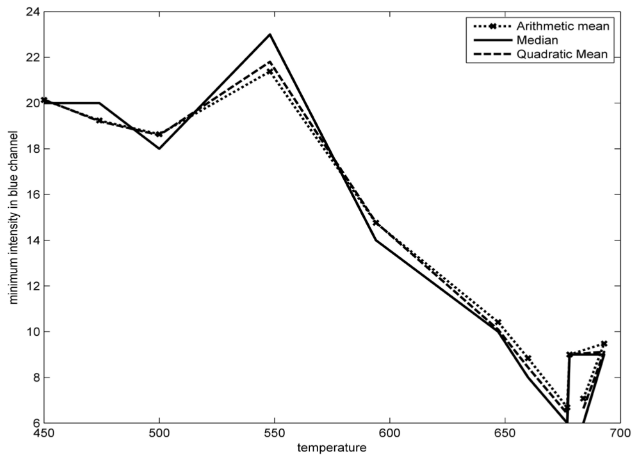

Figure 11. Minimum intensity of blue channel grey levels versus boiler temperature.

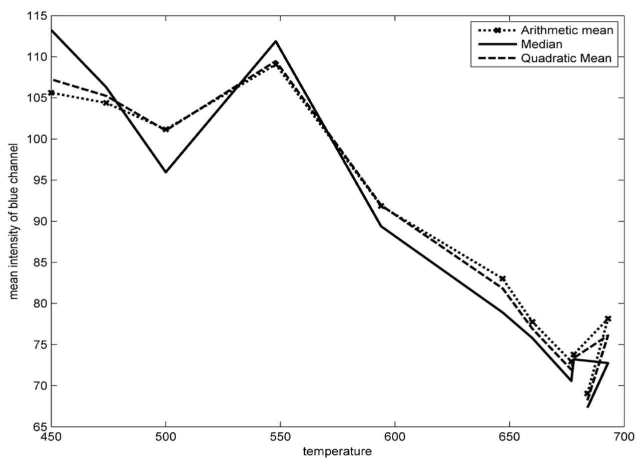

Figure 12. Mean intensity of blue channel grey levels versus boiler temperature.

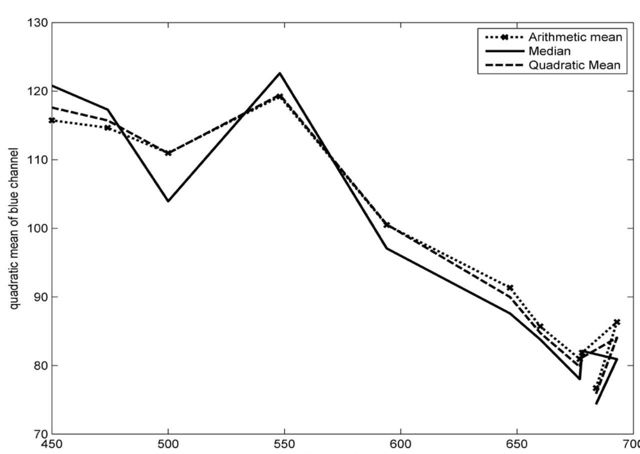

Figure 13. Quadratic mean of blue channel grey levels versus boiler temperature.

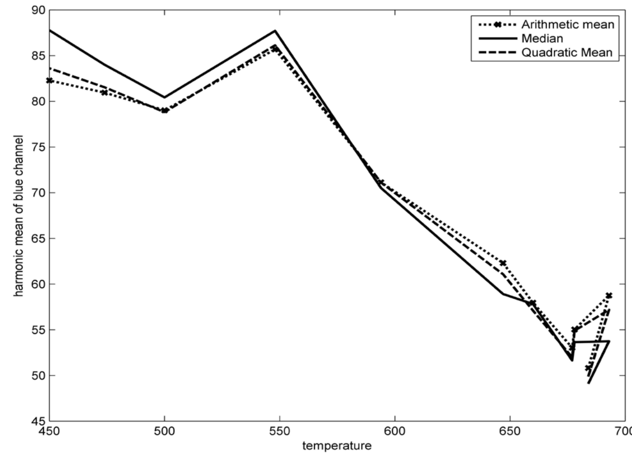

Figure 14. Harmonic mean of blue channel grey levels versus boiler temperature.

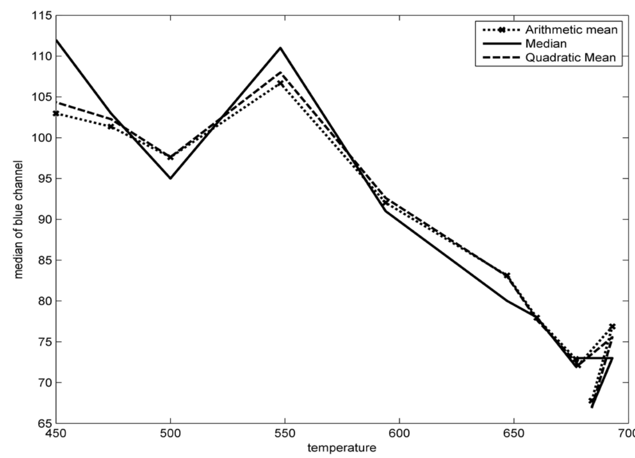

Figure 15. Median of blue channel grey levels versus boiler temperature.

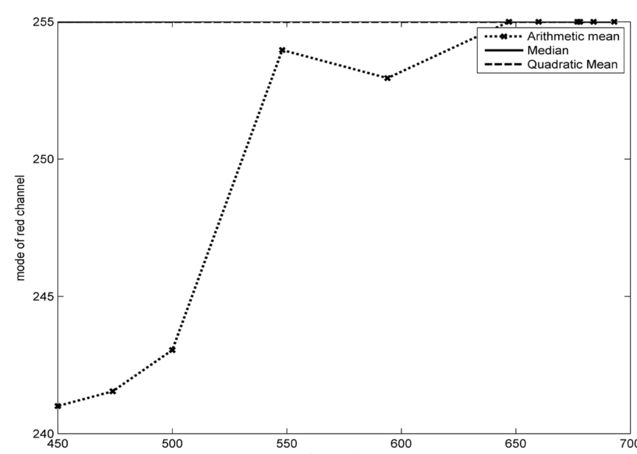

Figure 16. Mode of red channel grey levels versus boiler temperature.

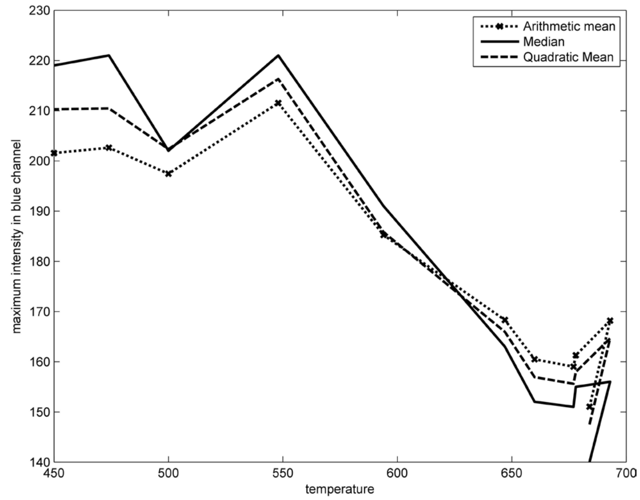

Figure 17. Maximum intensity of blue channel grey levels versus boiler temperature.

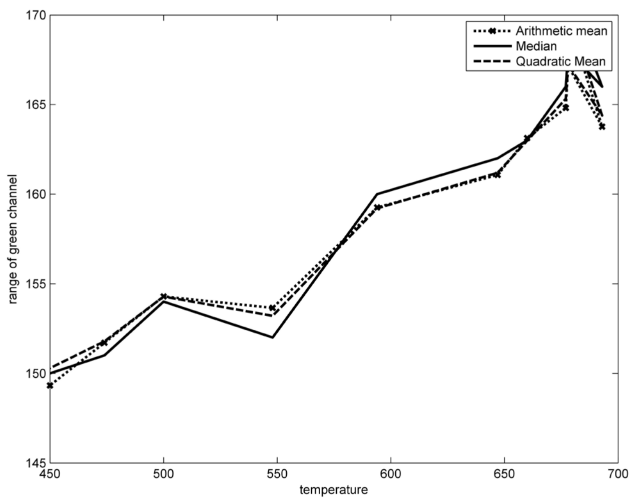

Figure 18. Range of green channel grey levels versus boiler temperature.

influence of outliers, caused by the flame turbulence. Even though the influence of outliers due to the turbulence of the flame is expected, quadrature, arithmetic mean and median of the individual frame features do not exhibits significant deviations. The measures of central tendency and dispersion of blue channel grey level decay significantly with increase in combustion air flow and boiler temperature. More interestingly the slope of decay increases substantially as the boiler temperature reaches its optimum value.

Maximum intensity of the red channel reaches, its saturation, '255', early before the optimum boiler temperature. Hence maximum intensity of the red channel cannot be used to identify the optimum combustion air flow. But the mode of the red channel reaches its saturation only at optimum airflow and maximum boiler temperature. Mode of red channel grey levels is the grey level with maximum probability density in the red channel. From the Figure 16, it is perspective; the feature, mode of red channel outperforms the rest of feature vectors in effectively portraying the optimum combustion air flow.

From the Figure19, it is evident that the boiler temperature falls after and before 35% opening of the air inlet valve. Hence the optimum airflow and optimum combustion is expected to be at 35% air inlet valve opening.

The Table 1 contain the range of video segment features corresponding to the optimum boiler temperature and combustion air flow. But surprisingly even for a video of diesel flame of extreme turbulence, arithmetic mean, median and quadratic mean of individual frames in the video segment are roughly equal. This means that the procedure itself is not prone to outliers. The range of features of the video segment corresponding to optimum boiler temperature shown in Table 1 is the arithmetic mean of individual frame features. The numerical values of standard deviation, variance and MAD of the blue channel grey level features of video segments furnished in Table 1 and visual inspection of the Figure 8 to Figure 10 reveals that the optimum boiler temperature is maintained when the standard deviation, variance and MAD are below 32.95, 1293 and 30.38, respectively. Below this threshold, the measured boiler temperature is above 684 degree centigrade. The maximum boiler temperature reached is

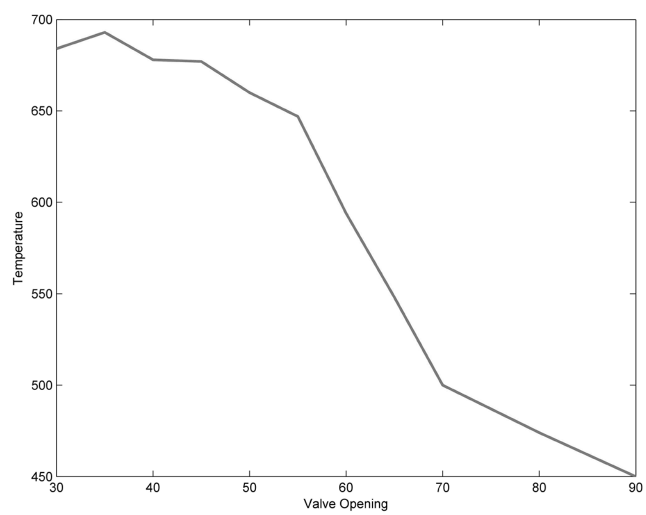

Figure 19. Temperature versus valve opening.

6930C. The optimum boiler temperature is an arbitrarily defined range between 6840C and the maximum boiler temperature.

The spread is not an apt feature to characterise the combustion efficiency in diesel fired boiler and the spread exhibit an inter frame dispersion with a mean of 99862 pixels and standard deviation of 44861. Fall in standard deviation and variance of grey levels in the blue channel conform that the blue intensities get converged to the minimum range as the emission spectrum get shifted to IR.

Pearson correlation coefficients among boiler temperature and flame features are exhibited in Table 2 and Table 3. Table 3 comprises Pearson Correlation Coefficient for video features which are less correlated with boiler temperature and Table 2 demonstrates Pearson Correlation Coefficient for highly correlated video features. The video features exhibiting Pearson Correlation Coefficient above 0.9 is referred as highly correlated in this context. The video features of blue channel grey levels are linearly correlated to boiler temperature. Range of green channel grey levels, IQR, variance and MAD of blue channel grey levels exhibits correlation close to -0.96.

Table 2. Pearson correlation coefficient between boiler temperature and highly correlated flame features.

Flame features	Pearson correlation coefficient
Arithmetic mean of blue channel	–0.9302
Geometric mean of blue channel	–0.9276
Harmonic mean of blue channel	–0.9263
Quadratic mean of blue channel	–0.9329
Median of blue channel	–0.9166
Median of red channel	0.9298
Mode of red channel	0.9182
Mode of blue channel	–0.9242
Minimum grey level of blue channel	–0.9318
Maximum grey level of blue channel	–0.9059
Range of green channel	0.9679
Inter quartile range of blue channel	–0.9630
Standard deviation of blue channel	–0.9442
Variance of blue channel	–0.9624
Mean absolute deviation of blue channel	–0.9503

Table 3. Pearson correlation coefficient between boiler temperature and less correlated flame features.

Flame features	Pearson correlation coefficient
Arithmetic mean of green channel	–0.1772
Arithmetic mean of red channel	0.8976
Geometric mean of green channel	0.8976
Geometric mean of red channel	0.8936
Harmonic mean of green channel	–0.2846
Harmonic mean of red channel	0.8884
Quadrature mean of green channel	–0.1410
Median of green channel	–0.2823
Mode of green channel	0.4451
Minimum grey level of green channel	–0.6735
Minimum grey level of red channel	0.7325
Maximum grey level of green channel	–0.8208
Maximum grey level of red channel	0.8628
Range of blue channel	–0.8926
Range of red channel	–0.5804
Inter quartile range of green channel	0.8602
Inter quartile range of red channel	0.1870
Standard deviation of green channel	0.8732
Standard deviation of red channel	–0.1365

6. Conclusion

The correlation between the features extracted from flame video and the boiler temperature is statistically evaluated. The measure of central tendency and dispersion of blue channel grey levels are correlated more linearly to boiler temperature than red and green channel grey levels. However the range of green channel grey levels and mode of red channel grey levels exhibited appreciable correlation, almost similar to the blue channel features.

The value of the Pearson correlation coefficient ensures that the video features are linearly related to the boiler temperature. Hence these features can be employed for flame temperature measurement and video based combustion control.

7. Future Scope

The boiler temperature depends equally on combustion efficiency and the rate at which the heat is swept away from the boiler. The latter is directly related to air flow rate.

Hence, the boiler temperature alone, is not an effective indicative for optimum combustion, rather, flue exhaust analysis along with the boiler temperature would be an apt solution, to identify the optimum airflow which offers perfect combustion of air-diesel mixture and maximum flame temperature. The temperature profile of any flame is heavily correlated to the IR spectrum, emitted from the flame than the visible energy. The dependency of blue channel grey level variations over the IR spectral changes may also be evaluated further. A mathematical relation can be established between correlated video features and boiler temperature. The relationship between features extracted from the video of the flame and boiler temperature may be confirmed at different fuel inlet rate also.

7. Reference

1. Cencerrado G, Pellicer A P, Martínez B G, and Rubio A B. Digital image processing for analysis of flame characteristics and stability, [Online]. Accessed on 11/03/2011; Available from: http://teide.cps.unizar.es:8080/pub/publicir.nsf/codigospub/0716/$FILE/cp0716.pdf.
2. Luo Z, Zhou H C. A combustion-monitoring system with 3-D temperature reconstruction based on flame-image processing technique, IEEE Transactions on Instrumentation and Measurement. 2007; 56(5):1877–82.
3. Bheemul H C, Lu G, Yan Y. Digital imaging-based three-dimensional characterization of flame front structures in a turbulent flame, IEEE Transactions on Instrumentation and Measurement, 2005; 54(3):1073–78.
4. Brisley P M, Lu G, Yan Y, Cornwell S. Three dimensional temperature measurement of combustion flames using a single monochromatic CCD camera, Proc. 21st IEEE Instrumentation and Measurement Technology Conference. 2005; 54(4):1417–21.
5. Zhou H C, Lou C, Cheng Q, Jiang Z, He J, Huang B, Pei Z, Lu C. Experimental investigations on visualization of three-dimensional temperature distributions in a large-scale pulverized-coal-fired boiler furnace, Proceedings of the Combustion Institute. 2005; 30 (1):1699–706.
6. Lu G, Yan Y, Colechin M. A digital imaging based multifunctional flame monitoring system, IEEE Transactions on Instrumentation and Measurement. 2004; 53(4):1152–58.
7. Jiang ZW, Luo ZX, Zhou HC. A simple measurement method of temperature and emissivity of coal-fired flames from visible radiation image and its application in a CFB boiler furnace, Fuel. 2009; 88(6):980–87.
8. Lu G, Yan Y, Cornwell S, Riley G. Temperature profiling of pulverized coal flames using multi-colour pyrometric and digital imaging techniques, IEEE Transactions on Instrumentation And Measurement. 2006; 55(4):1303–308.
9. Wang X, Wu Z, Zhou Z, Wang Y, Wu W. Temperature field reconstruction of combustion flame based on high dynamic range images, Optical Engineering. 2013; 52:43601:1-43601:10.
10. Sujatha K, Venmathi M, Pappa N. Flame monitoring in power station boilers using image, ICTACT Journal on Image and Video Processing. 2012; 02(04):427–34.
11. Lou C, Zhou HC. Deduction of the two-dimensional distribution of temperature in a cross section of a boiler furnace from images of flame radiation, Combustion and Flame. 2005; 143:97–105.
12. Bodkhe RG, Nandurkar YY, Akant SS, Bankar SL, Performance analysis of separating and throttling calorimeter to determine quality of steam on thermax diesel fired water tube boiler, International Journal of Research in Engineering and Applied Sciences (IJREAS). 2014; 02(01):41–5.
13. Otsu N., A threshold selection method from gray-level histogram, IEEE Transactions on Systems, Man, and Cybernetics. 1979; 9(1):62–66.