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DEVELOPMENT OF A VIDEO SIGNAL BASED NON-INVASIVE METHOD FOR MEASUREMENT OF TURBULENT FLAME TEMPERATURE

Abi P. Mathew[1], A. Asokan[2] and K. Batri[3]
[1]Department of Instrumentation, Annamalai University, Tamilnadu, India
[2]Department of Instrumentation, Annamalai University, Tamilnadu, India
[3]Department of Electronics and Communication Engineering, PSNA College of Engineering and Technology, Dindigul, Tamilnadu, India
E-Mail: abimthw@gmail.com

ABSTRACT

Present investigation explores the application of video processing in non-contact type temperature measurement for turbulent flames. Average flame features for a small time period are compared with actual flame temperature to establish a correlation. Features like spread, intensity of red, blue and green component are taken up for detailed study. The limitation of image processing method for flame feature extraction in a pressurised fuel supplied low capacity boiler is also revealed through this experimental research. Through this comparative study it is indicated that when combustion is highly turbulent in nature, images may not represent the actual condition; instead average features of image frames from videos of this turbulent process for short period of time can be considered as a better option for representing the condition of process. Video of turbulent flame for a short period of time is separated into time dependent picture frames for detailed study. Analysis of picture frames reveals the volatile nature of features, frame by frame. Experiments are conducted on a 25 liters diesel fired boiler prototype and analysis of video of flickering flame is done by Matlab®.

Keywords: flame image processing, turbulent flame analysis, combustion model, flame video processing, non-contact temperature measurement.

INTRODUCTION

Digital technologies are major contributors in manufacturing automation and productivity improvement, especially in monitoring and control functions (A Gunassekaran *et al.,* 1999). Industry uses different types of boilers for steam generation. Measurement of combustion temperature inside their furnaces is a primary input for achieving high efficiency through effective control of the fuel-air mixture. Direct measurement of the flame temperature is at present the most common method which may not provide an accurate measure due to the turbulent nature of the furnace flame. Temperature estimation can be made by assessing certain features of the flame image (Z. Jiang *et al.,* 2009). Computer based analysis of flame images is thus a good solution for fast and precise non-contact type temperature measurements. In boilers with pressurised fuel supply, the turbulent flame inside their furnaces makes temperature measurement from the features of the instantaneous images very unreliable.

This article presents a method for temperature measurement by a computer based analysis of video images of the turbulent flame in a vertical boiler. For this analysis, the video of the flame for a short period of time is recorded and the images are separated from the video, frame by frame. First, a study of the variations in features among these frames is carried out. Their mean values for the entire set of image frames are then subjected to the analysis. A comparison of maximum and minimum values of the features among the image frames is made and the mean values of these features are determined to analyse the competency of the image and the video to represent the quality of flame. The red component of the video is used to estimate the temperature generated from the flame.

The investigations in this field by other researchers are briefly narrated in section 2. Section 3 describes the experimental configuration and the parameters adopted for analysis in the present study. In section 4 the separation of image frames from video and, localising and extracting spreads as well as the intensities of red, green and blue components, are explained. Experimental results are analysed, in detail, in section 5 and conclusions of this experimental research are listed in section 6. Section 7 looks at future research areas in this field.

LITERATURE REVIEW

Combustion flame detection, characterisation and temperature monitoring by image/video processing are studied by many researchers. Flame image-based burning state recognition system using a set of heterogeneous features and fusion techniques (Li *et al.,* 2012), modelling the variations of directional brightness temperature (DBT) for row-structure crops with the images captured by a large-aperture thermal infrared camera over a maize canopy (Yu *et al.,*2004), Hidden Markov model (HMM) for predicting flame combustion condition in furnace (Zhang *et al.,* 2006), three dimensional dynamic flame temperature field reconstruction from flame images (Wang *et al.,*2013), exploring the interdependence of combustion efficiency with concentrations of SOx, NOx, CO2 in flue gas and air fuel ratio using an Infrared camera to capture the flame video (Sujata *et al.,* 2013) are some of the attempts made by researchers to use video/image for characterisation and temperature monitoring.

Flame analysis can be done by analysing the video or still images of the flame. Flame videos are used mostly to identify the changes in the structure of flame. Video signals are also used extensively for flame detection. In most of the studies, changes in certain features of video in a frame by frame analysis prove the occurrence of flame. Images of flame inside a boiler are used to analyse the combustion efficiency of boiler. The quality of flame varies with the variation in air fuel mixture. In a boiler combustion efficiency is maximised when the right combination of the air fuel mixture is supplied. Pressurised supply of low viscous fuels like diesel creates a very turbulent flame which causes erroneous results when still images are processed.To overcome this, instead of still images videos of the flame can be captured for the processing. A new computer-based method for estimating the combustion temperature in a boiler, supplied with high pressure fuel, using video images is developed and experimentally verified. This work is presented in the following sections.

EXPERIMENTAL CONFIGURATION

Experimental set-up consists of a boiler which uses diesel as its fuel, CCD camera for recording video and computer for processing the acquired signals, as given in Figure-1. For study purpose, a diesel boiler of 25 litre capacity is used as a prototype (Figure-2) of real boilers with large capacities. The specifications of the boiler are shown in Table-1. Video signals of the flame in the boiler are recorded directly through the sight glass at the top of the boiler using a CCD camera of high quality. Boiler flame temperature is recorded with a thermocouple which is inserted directly into the flame.

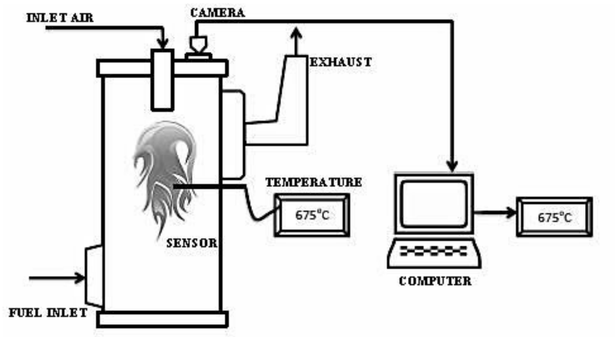

Figure-1. Experimental set-up.

During the experiment the boiler recorded a maximum flame temperature of 675^{0}C and steam temperature of 165^{0}C while in operation. Maximum inlet air flow recorded was 10 m3/hour and maximum fuel flow was 18kg/hour at 12kg/cm^2(1.18 MPa) gauge pressure. 15 Video segments for 5 seconds each were recorded at different inlet air flow-fuel flow ratios.

Table-1. Specifications of boiler used.

Parameter	Unit	Value
Steam output	kg/h	300
Heat output	M.W	0.188
Fuel consumption	kg/h	18
Burner control	On/Off	
Blower motor	kW	0.75
Fuel pump motor	kW	0.37
Total heating surface	m^2	5.9

Figure-2. Diesel fired boiler prototype.

Video recorded from the boiler is analysed using Matlab®. Image frames from the recorded video are extracted and stored separately for further analysis. As the grey level intensities at the flame region are higher than the other image regions, Otsu's thresholding is used to separate the flame region.

The mathematical strategy adopted for estimating optimum threshold is as,

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

$$\mathrm{P_i} = {}^{\mathrm{n_i}}/_{\mathrm{N}}\ \mathrm{P_i} \geq 0, \qquad \sum_{i=1}^{L} \mathrm{p_i} = 1 \tag{1}$$

where N is the total number of pixels in the greyscale frame , n_i 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,

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

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

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

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

$$\mu(k) = \sum_{i=1}^{k} ip_i \tag{6}$$

where $\omega(k)$ and $\mu(k)$ are the zeroth and first order cumulative moments of the histogram up to the kth level, respectively.

$$\eta(k) = \sigma_B^2(k)/\sigma_T^2 \tag{7}$$

$$\sigma_B^2(k) = \frac{\left[\mu_r \omega_{(k)} - \mu_{(k)}\right]^2}{\omega_{(k)}\left[1 - \omega_{(k)}\right]} \tag{8}$$

Where η is total variance level, σ_B^2 is between class variance

$$(k^*) = \max_{1 \le k < L} \sigma_B^2(k) \tag{9}$$

The optimal threshold, k maximizes with in L-class, between L-class or total variance as in (3).

INVESTIGATION METHODOLOGY

Flame video records are separated into image frames and mean values of primary (red, green and blue) colour intensity components. These, along with the property of spread, are considered for examination. These features are extracted and separated from images for assessment of their correlation with temperature. During the study, the uneven distribution of features along the whole spectrum of image frames are also evaluated to demonstrate the limitations in the reliability of instantaneous still images as the source for flame temperature estimation.

Spread

'Spread' estimates the area of all of the 'on' pixels in an image by summing up the areas of each pixel in the image. For numeric input, any non-zero pixel is considered to be 'on'. Spread is calculated from the binary image of the flame after the application of thresholds. Variations in flame intensities in different image frames result in different spread values for the flame image frames (see Figure-3). Maximum value and minimum value of spread among these image frames and the mean value of spread are calculated for analysis.

Colour components in image frames

The intensities of the colour components over the image frames are estimated, segmented and binary images are extracted for all the image frames. Maximum and minimum values of these colour intensities among the image frames and the mean value of colour component in the image frames are calculated for analysis. Original RGB image of 144th frame of the captured video is shown in Figure-4 where the red, blue and green components are shown separately too.

The 144 image frames extracted from the video is localised for the flame region and the binary images are developed by thresholding the localised image. Random images are chosen from the localised flame area as spread (see Figure-3). Red Blue and Green colour components of the colour images are separated from the image frames. These localised image frames are then segmented to calculate the maximum, minimum and mean values of each colour component of the image frames.

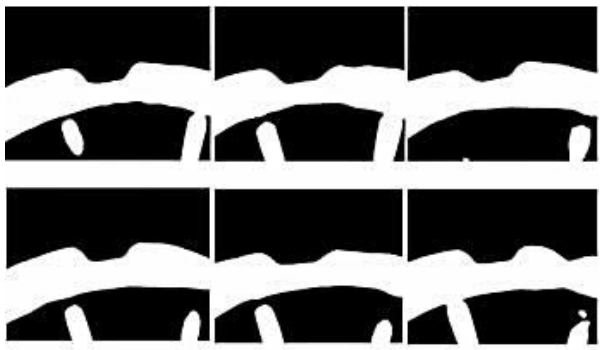

Figure-3. Random image frames of spread.

Comparison of boiler flame temperature with image features of flame

Boiler temperatures directly recorded using the thermocouple at different inlet air- fuel ratios are compared with the image features of red, blue and green components for establishing a relationship. A mathematical model of the relationship is developed for verifying the effectiveness of using mean values of the correlated features from video. This is then compared with the image feature of that particular instant to demonstrate the enhanced reliability of video processing in boiler flame analysis.

EXPERIMENTAL RESULTS

Competency of video over still image for flame feature analysis

Distribution of features among frames of flame video is highly unsteady and only very few consecutive frames are similar in nature as can be seen from Figure-4.

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Spreads of flame intensity of red, blue and green components of the frames are quite different, indicating the volatile nature of the flame video. There is a visible variation in maximum and minimum values of different features from mean value.

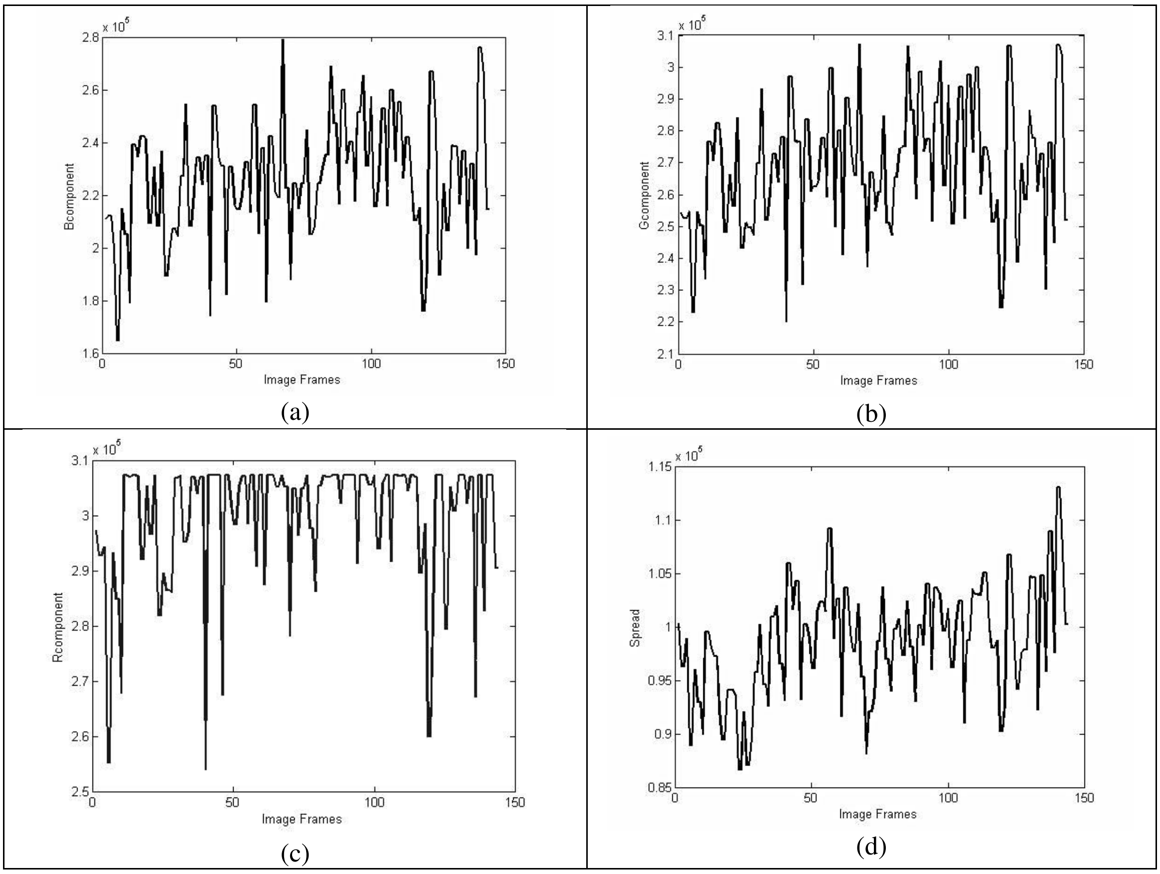

Figure-4. (a) Distribution of Blue component over 144 image frames, (b) Distribution of Green component over 144 image frames, (c) Distribution of Red component over 144 image frames (d). Distribution of spread over 144 image frame.

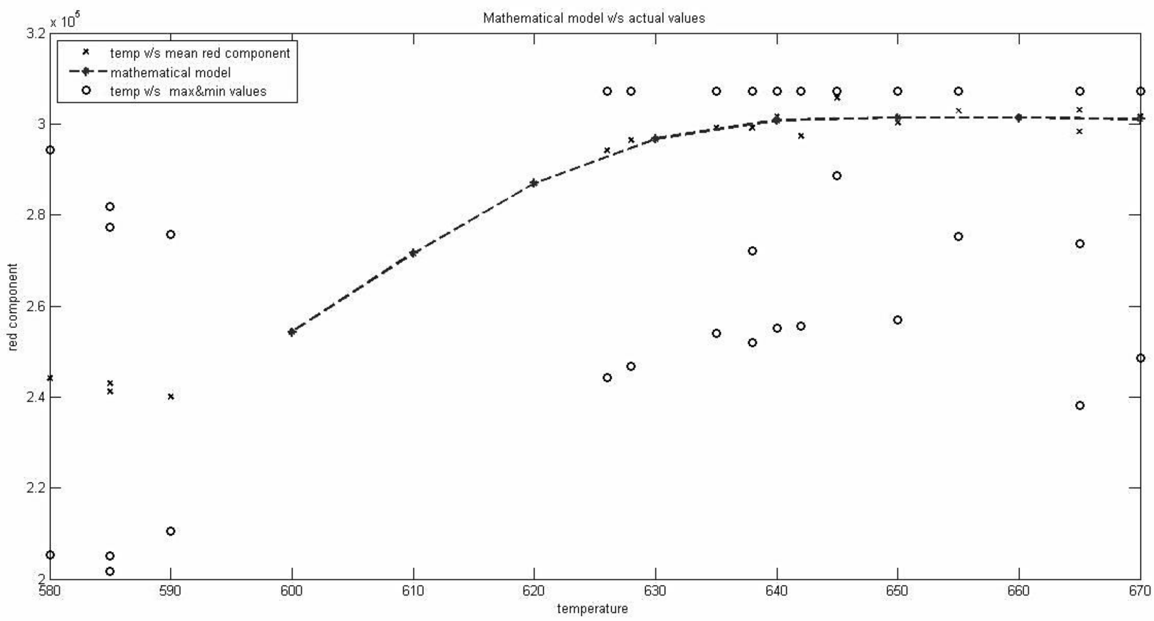

Figure-5. Mathematical model versus actual red component values.

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Table-2. Values of different features amongst 144 image frames of a video.

Parameter	Mean value	Maximum value	Minimum value
Spread	98489	113040	86666
Red Component	299200	307200	254000
Green Component	268170	307200	219963
Blue Component	225800	279230	164620

Variation in mean values and the maximum, minimum values of spread and colour intensities as shown in Table-2 is also a measure of the incompetency of using still images for analysing flame features.

Table-3. Values of different features of first 10 picture frames of the video.

	Spread	R Component	G Component	B Component
1	100304	297260	254210	210990
2	96228	292643	252410	212060
3	96228	292643	252410	212060
4	98932	294350	254650	199900
5	88928	255160	222950	164620
6	88928	255160	222950	164620
7	95976	293200	254628	215040
8	92899	284860	250130	205070
9	92899	284860	250130	205070
10	89913	267870	233530	179130
	98489	299200	268170	225800

Table-3 is a comparative analysis of the first 10 picture frames extracted from the video. Consecutive picture frames of the flame video do not have the same values for spread or the intensity of colour components. The results of analysis of consecutive flame images clearly show the uneven nature of distribution. The graph representing the mean red component, maximum and minimum values of red component and the mathematical model result is shown in Figure-7.

Table-4. Correlation between flame temperature and colour components of image.

Temperature	Red component	Green component	Blue component
635	299200	268170	225800
638	299050	268050	222310
650	300220	270020	224280
665	303030	270670	225780
640	301530	267350	219960
628	296380	266690	222570
626	294170	265600	221170
642	297410	271270	227870
665	298300	272460	227430
670	301620	282930	237380
655	302830	278870	227000
585	241190	258910	173210
590	240110	265600	169470
580	244060	271270	170180
585	242940	272460	165960
645	305780	282930	236440
638	299110	278870	277350
Correlation Coefficient	0.923479695	0.516846874	0.81965095

Figure-5 clearly shows that mean value of red component is always dependable than instantaneous values. The instant values fluctuate wildly between minimum and maximum values. Such fluctuations make the analysis using image (image frame of video) un reliable and mean values of features taken from video are the better choice for flame analysis of boilers with high pressure fuel supply.

Non-contact type temperature estimation using video

Certain features extracted from video of flame show good correlation with the actual flame temperature. Red colour component extracted from the video of flame shows maximum correlation of 0.923 as shown in Table-4.

Mathematical model of relationship between temperature and red colour component is as follows.

$$y = (-1.21 \times 10^{-6})x^6 + (4.48 \times 10^{-3})x^5 - (6.85)x^4 + (5574.48)x^3 - (2.55 \times 10^6)x^2 + (6.17 \times 10^8)x - 6.23 \times 10^{10} \quad (10)$$

where y represents the red component and x represents temperature.

This model can be used to estimate temperature of flame in place of direct contact type measurement methods. The credibility of this temperature estimation method is validated by the experiments and it can be stated that this method is suitable for fast temperature estimation of turbulent combustion flames.

CONCLUSIONS

The results of analysis of flame images prove the need for taking mean values of features from the consecutive image frames. Mean value of features extracted from consecutive image frames of the video of flame is a better option for temperature measurement and/or control of combustion flames in boilers which use pressurised low viscous fuels like diesel. Thus it is proved that when the flame is highly turbulent in nature, it is always better to consider video for studying the flame.

Temperature of the flame is highly correlated with mean red component values of the video. Mathematical model of relationship between temperature and average red colour component can be used as a reliable non-contact type temperature measurement method for turbulent flames.

FUTURE SCOPE

This study can be taken forward for modelling a combustion control system. Estimation of the right proportion of inlet air and fuel mix for most efficient combustion may be done for developing automatic control systems in boilers and other furnaces.

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