COMPUTER IMAGE PROCESSING AND NEURAL NETWORK TECHNOLOGY FOR BOILER THERMAL ENERGY DIAGNOSIS

by

Qinghong WU*

School of Electronic and Information Engineering,
University of Science and Technology Liaoning, Chenyang, China

Original scientific paper
https://doi.org/10.2298/TSCI191012080W

The paper uses the flame image processing technology to diagnose the furnace flame combustion achieve the measurement of boiler heat energy. The paper obtains the combustion image of the flame image processing system, and extracts the flame image characteristics of the boiler thermal energy diagnosis, constructs the neural network model of the boiler thermal energy diagnosis, and trains and tests the extracted flame image feature parameter values as the input of the neural network. A rough diagnosis of the boiler's thermal energy is obtained while predicting the state of combustion. According to the research results, a boiler thermal energy diagnosis system was designed and tested on the boiler of 200 MW unit. The experimental results confirmed the applicability of the system, which can realize on-line monitoring of boiler heat energy and evaluate the combustion situation.

Key words: *furnace flame, temperature field, combustion diagnosis, artificial neural network, image processing*

Introduction

In the operation of power plant boilers, fire extinguishing and coking caused by combustion system failure are one of the main threats to the safe operation of boilers. Therefore, timely detection of faults, prediction of fire extinguishing, and avoiding coking are the main objectives of combustion fault diagnosis. From the operating experience of the power station, the center position, temperature and distribution of the furnace flame are the focus of combustion diagnosis.

At present, the flame detection equipment installed on the boiler in China generally can only detect the strength of the flame, and the detection of the temperature field can only be limited to a limited point in the furnace, and the on-line detection of the temperature field distribution in the furnace cannot be realized. It is also impossible to evaluate the boiler flame condition. With the development of computer technology and the improvement of industrial CCD devices, temperature field measurement and combustion diagnosis based on image processing technology have received extensive attention. At present, flame image acquisition, processing, temperature field measurement and reconstruction have been achieved. Preliminary progress. Artificial neural networks have been applied to the diagnosis of flame image combustion in China, and experimental research has been carried out in practice [1].

* Author's e-mail: qingwu28193451@163.com

Hitachi's HIACS3000 system, introduced in 1985, uses the furnace flame image recognition technology [2], which can be used to estimate the distribution of the flame temperature field, the estimation of combustion economy, and the estimation of NO_x emissions. This is to stabilize boiler combustion and improve combustion. Efficiency has important implications. The scientific and technical personnel of Huazhong University of Science and Technology used the reference point method to calculate the 2-D temperature field from the distribution of flame radiation energy by means of the radiation law, and diagnosed the combustion condition according to the information of the temperature field [3]. Researchers at Shanghai Jiaotong University used image fiber and CCD to obtain a single burner flame image. After image card processing, the pseudo color display combined the flame characteristics with the burner's switching state to reflect the combustion state and stability of the furnace [4]. Kefu of Nanjing Electric Power Automation Institute deduced the flame radiation temperature measurement formula and extracted the feature quantity of each torch image [5]. The researchers of Southeast University obtained the image characteristics of combustion steady-state and transient process, and carried out combustion flame stability. Research on the mechanism of sex and recognition [6]. Thus, a common discrimination of full furnace fire extinguishing and full furnace flame image confirmation was proposed to detect flame extinction.

Based on the principle of three primary color temperature measurement and neural network theory, combined with digital image processing technology, this paper proposes a method of temperature field measurement and combustion diagnosis, and develops temperature field detection and combustion diagnosis on a 200 MW unit boiler of a power plant. The (measurement) system was tested and preliminary results were obtained.

Temperature measurement principle

Based on the meteorological data of the design year, the crop water demand calculation is carried out. Crop water requirements are calculated using the Penman formula recommended by the UN Food and Agriculture Organization for the year. The crop water requirement is the product of the potential evaporation and the corresponding crop coefficient.

In the range of radiation wavelength less than 1000 nm and temperature below 3000 K, according to the Wien approximation of the Planck formula, the spectral radiant energy of a small region in a high temperature furnace can be expressed [4]:

$$M\left(\lambda,T\right)=\varepsilon\left(\lambda\right)\frac{C_1-\dfrac{C_2}{\lambda T}}{\lambda^{5e}} \tag{1}$$

where $M(\lambda, T)$ represents the radiant energy of wavelength λ, T – the thermodynamic temperature, and C_1, C_2 – the first and second radiation constants, respectively. As can be seen from [5], in the image formed by the color CCD camera, the chromaticity values R, G, and B of any pixel are a function of the spectral radiance of the pixel display:

$$\begin{aligned}
R_e &= k_R\int_{320}^{780} M\left(\lambda,T\right)\eta_R\left(\lambda\right)\mathrm{d}\lambda \\
G_e &= k_G\int_{320}^{780} M\left(\lambda,T\right)\eta_G\left(\lambda\right)\mathrm{d}\lambda \\
B_e &= k_B\int_{320}^{780} M\left(\lambda,T\right)\eta_B\left(\lambda\right)\mathrm{d}\lambda
\end{aligned} \tag{2}$$

where $\eta_R(\lambda)$, $\eta_G(\lambda)$, and $\eta_B(\lambda)$ is the spectral response function of the three channels R, G, and B, respectively. The $k_i = (R, G, B)$ is the gain of each channel of the system, which can be obtained by eq. (3):

$$\begin{aligned}\frac{R_e}{G_e} &= \frac{k_R \int\limits_{320}^{780} M(\lambda,T)\eta_R(\lambda)\mathrm{d}\lambda}{k_G \int\limits_{320}^{780} M(\lambda,T)\eta_G(\lambda)\mathrm{d}\lambda} \\ \frac{G_e}{B_e} &= \frac{k_G \int\limits_{320}^{780} M(\lambda,T)\eta_G(\lambda)\mathrm{d}\lambda}{k_B \int\limits_{320}^{780} M(\lambda,T)\eta_B(\lambda)\mathrm{d}\lambda}\end{aligned} \tag{3}$$

The temperature T can be obtained according to the eq. (3), and the aforementioned formula is simplified in [6]:

$$T = \frac{G_2\left[\dfrac{2}{\lambda_G} - \dfrac{1}{\lambda_R} - \dfrac{1}{\lambda_B}\right]}{\ln\dfrac{R_e G_e}{B_e^2} + 5\ln\dfrac{\lambda_R\lambda_B}{\lambda_G} + \ln\dfrac{\varepsilon_R\varepsilon_B}{\varepsilon_G^2} + \ln\dfrac{k_R k_B}{k_G^2}} \tag{4}$$

Characterizing the characteristic parameters of the furnace flame combustion state

Image preprocessing

Due to the dark current, smear, halo and other reasons of the CCD camera, the image will be blurred, and the image signal will pass through multiple conversion links, which will generate some high frequency components, which will cause the appearance of Moir interference fringe [7], plus the video signal in the transmission process. Various interfering signals are also introduced, so these images must be pre-processed to reduce measurement errors. First, using inter-frame averaging, several images acquired at the same time are averaged by pixel points, a pair of images are synthesized, and then the averaged image is subjected to median filtering. Median filtering is a non-linear signal processing technique that has a good suppression of random noise in the image and better protection of the contour and edges of the image. In addition, the median filter has no influence on the step signal, maintains the spectrum after filtering, and has a strong removal effect on the salt and pepper noise on the image. The median filtering of the image first selects a suitable 2-D window. After several experiments, a 3×3 square filtering window is used.

Feature value extraction

The 2-D temperature field corresponding to the full furnace flame image collected by the CCD at a certain time can be obtained by the colorimetric temperature measurement method, but the temperature field is substantially the cumulative superposition of the 3-D temperature field in the furnace on the CCD photosensitive target surface, which is not It reflects the temperature change information of the furnace space along the height direction, but it can well reflect the distribution characteristics of the flame in the 2-D space, so it is called the diagnosis temperature field. At present, under the condition that the 3-D temperature field reconstruction in the furnace cannot meet the real-time condition, the 2-D diagnostic temperature field can be

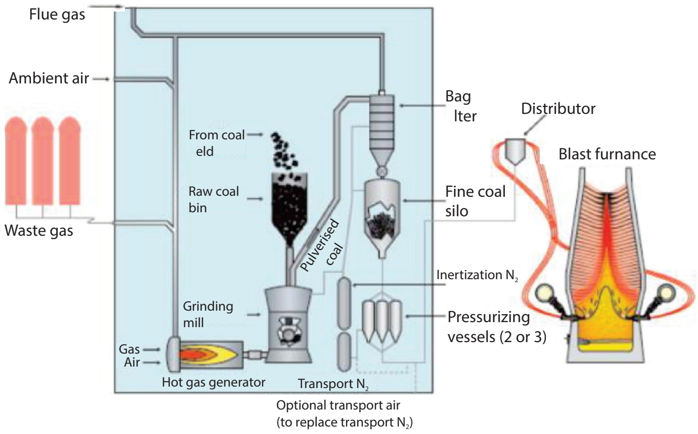

Figure 1. Three combustion stages of pulverized coal jet

used to obtain important combustion state information, and the combustion diagnosis is performed accordingly.

The flame image is collected by a furnace image flame treatment system installed at the burner exit of a 300 MW unit boiler of a coal-fired power plant. The flame image at the exit of the pulverized coal burner is shown in fig. 1. As can be seen from the figure, a tongue-shaped dark black wind coal mixture is first ejected from the burner. The pulverized coal combustion is divided into three-stages along the jet direction: in the unburned area, the pulverized coal and the primary air are sprayed from the burner. At this time, the pulverized coal temperature has not reached the ignition point and has not been burned. In the initial combustion zone, the pulverized coal is thermally decomposed by the high temperature radiation and the flame reflow in the furnace, and a large amount of volatile matter is precipitated and begins to burn violently. The particles are shiny. Since the main volatile matter and a small amount of coke particles burn at this time, the brightness has not reached the maximum, but the flicker frequency of the flame has reached the maximum value. This characteristic is used as an important basis for detecting the flame. In the complete combustion zone, the pulverized coal particles continue to penetrate. In the furnace, the volatiles precipitated at this time burned out, and the coke began to burn vi-

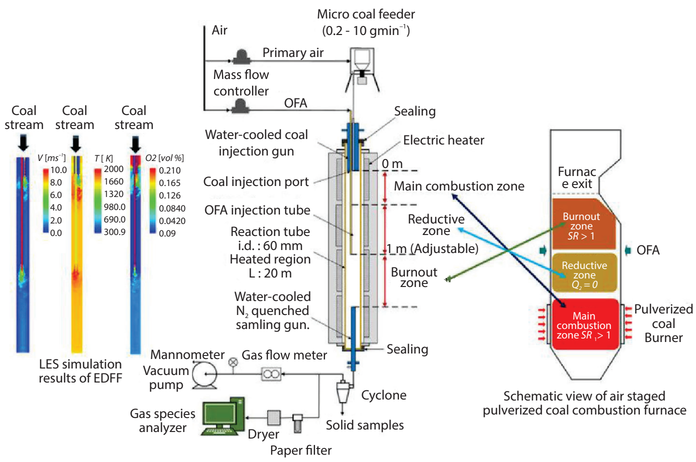

Figure 2. Combustion characteristic area and characteristic line of pulverized coal jet

olently, generating a large amount of heat, at which time the flame temperature and brightness reached a maximum.

In the image, a specific area indicating that coal powder is burning is referred to as a feature area. Through the repeated comparison of the experimental images, the characteristic area of the pulverized coal flame is drawn, and the middle line along the pulverized coal jet direction in the characteristic area is called the characteristic line, fig. 2. Feature areas and feature lines are important for the description of the flame.

Characteristic area average light intensity AvGrey

The average light intensity of all pixels in the feature area is an important criterion for the normal combustion of the flame. At the same time, the intensity of the light when the flame burns also reflects the temperature. When the flame is not burning normally, such as single-angle flameout, since the MFT does not move at this time, the pulverized coal will be sprayed into the furnace as usual. At this time, the average light intensity value will decrease, and the value is G1 by the test; if the whole furnace occurs. When the flame is extinguished, the average light intensity value will decrease, and the value is G2 measured by the test. In fact, G1 and G2 are different, and G1 > G2, because of the influence of other angular flame light intensity when the single angle is extinguished, the light intensity at this time will be greater than the light intensity when the whole furnace is turned off. Therefore, when the flame is burning normally, the average light intensity should be greater than G1.

Front position X

The frontal position on the feature line is another important criterion for the normal combustion of the flame. Observe the change in the luminance value on the characteristic line in fig. 2:

$$g_i = G_i + 1 - G_i \qquad (i = 0, 2, ..., K-1) \tag{5}$$

Where G_i is the pixel brightness value at position i on the feature line, and K is the total pixel on the feature line. Figure 3 shows the change in brightness of the flame. It can be seen that the brightness of the flame fluctuates greatly in the unburned zone and the initial combustion zone, and there is no significant change in the complete combustion zone. The change in flame brightness along the characteristic line has a distinct maximum, and the position of this maximum reflects the presence of the flame front.

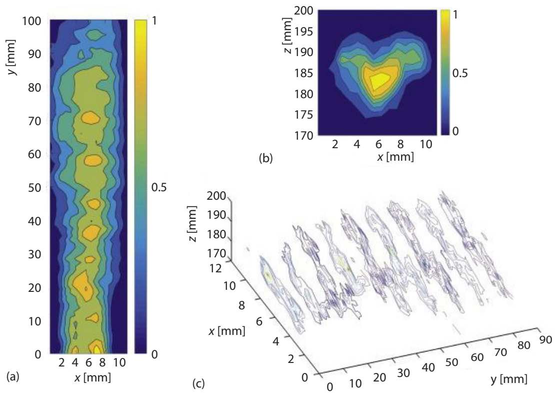

Figure 3. Pulverized coal flame front position

Defining the maximum value of the characteristic line g_i is the front position X of the flame. The front position is closely related to the combustion state. In normal combustion, the front position is at a certain distance from the burner exit. When the fire is extinguished, the pulverized coal is still being sprayed. At this time, the front position of the flame will be far from the burner outlet, and the position of the flame front at this time will be referred to as X_{max}. Thus, the criterion for the normal combustion state of the flame corresponding to the flame front is

$X \le X_{max}$. In addition, the pulsation of the pulverized coal flame is also an important feature of flame combustion. However, for the flame image processing system for online analysis, since the timeliness of the intelligent judgment is relatively high, the method of performing spectrum analysis after the FFT is changed by the timing signal is not feasible. Moreover, the pulsation of the flame is difficult to express with a certain amount. In view of this, in the characteristic parameters characterizing the combustion state, no parameters characterizing the flame pulsation are introduced. Thus, according to the previous analysis, there are two characteristic parameters for characterizing the burning state of the angular flame: the average intensity of the flame characteristic area and the position X of the flame front. To judge whether the angular flame combustion is normal, it is necessary to combine these two characteristic parameters to make a comprehensive judgment. Although the flame characteristic parameter reflects the change of the flame combustion state, there is no clear relationship between the characteristic parameter and the combustion state. Therefore, it is difficult to predict the trend of the flame combustion state from the characteristic parameters of the flame by the conventional method.

Average flame temperature

According to the deflagration theory, when the furnace temperature exceeds 750 °C, it can be guaranteed that furnace deflagration does not occur. Therefore, the average flame temperature reflects the real-time flame combustion intensity and combustion trend.

High temperature zone centroid co-ordinates and average temperature

When the four-corner combustion boiler is normally burned, it exhibits a characteristic that the brightness is gradually weakened from the center outward on the flame image. The image recognition method and the region segmentation technique are used to divide the image into several relatively uniform parts, and the average temperature of each part is determined to determine the centroid and area of the high temperature region. The boundary detection and region segmentation methods have region segmentation, merging, and growth algorithms that utilize geometric similarities between pixels [8]. The centroid of the high temperature zone can reflect whether the burning organization is reasonable. The average temperature in the high temperature zone is also an important parameter for combustion diagnosis. The temperature and distribution of the furnace influence the generation of NO_x. Local high temperature will generate a lot of NO_x, which plays a decisive role in the NO_x production in the whole furnace [9].

Temperature field distribution

It reflects the temperature field gradient of the flame diagnosis in the furnace, that is, reflects the change of the flame temperature on the 2-D plane, so that it can be understood whether the center of the flame is skewed, whether the four-corner burner has partial flameout or abnormal work, which can be reflected on the isotherm. Whether an angular temperature gradient is large.

Neural network based combustion diagnosis

Neural network structure

There are many kinds of neural network models. The so-called BP model, the error back propagation neural network, is the most widely used type of neural network model. The BP networks can learn many pattern mapping relationships without requiring any known mathematical function knowledge to describe the mapping between input and output. Mapping the input pattern to the desired output mode requires only the known mode pair training network, and by learning, the network has this mapping capability. This mapping of BP networks is a highly non-linear relational mapping. That is to say, the BP network can implement arbitrary mapping from the *M*-dimensional European space to the *N*-dimensional European space. Secondly, because BP algorithm can realize the learning of hidden layer units, it has strong information processing capability.

Structurally speaking, BP network is a typical multi-layer network. It is divided into input layer, hidden layer and output layer. The full interconnection mode is used between layers, and there is no interconnection between the same layer units. The connection weight of each layer can be adjusted by learning. The basic processing unit is a non-linear input-output relationship, and the following S-type action functions are generally selected:

$$f(x)=\frac{1}{1+\mathrm{e}^{-x}} \tag{6}$$

Figure 4 shows a typical BP network structure. In the figure, the first layer is the input layer, the *Q* layer is the output layer, and the middle layer is the hidden layer. Let the number of neurons in the qth layer $q = (1, 2,..., Q)$ be n_q, and the connection weight coefficient of the i^{th} neuron input to the qth layer be $\omega_{ij}^{(q)}(i = 1, 2,..., n_q, j = 1, 2,...,n_{q-1})$. The input-output transformation relationship of the network:

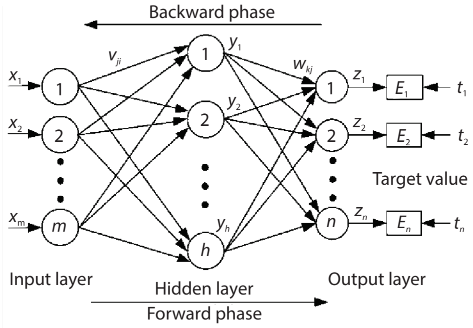

Figure 4. The BP neural network

$$\begin{gathered} S_i^{(q)}=\sum_{j=0}^{n_{q-1}}\omega_{ij}^{(q)}\chi_j^{(q-1)} \qquad \left[\chi_0^{(q-1)}=\theta_i^{(q)},\omega_{i0}^{(q)}=-1\right] \\ \chi_i^{(q)}=f\left[S_i^{(q)}\right]=\frac{1}{1+\mathrm{e}^{-\mu s_i^{(q)}}} \\ i=1,2,3,...,n_q \quad j=1,2,3,...,n_{q-1} \quad q=1,2,...,Q \end{gathered} \tag{7}$$

Network training

The author constructs a BP neural network model for predicting the combustion state through the characteristic parameters of the flame. Research shows that a three-layer network can complete the mapping from any *M*-dimensional space to *N*-dimensional space, so the network used is a 3-layer network with only one hidden layer in the middle.

In order to eliminate the effects of flame pulsation, the input of the BP network uses the following method: five frames of images are continuously acquired at each moment. Thus, the input sample of the network is the feature quantity of the flame image of five frames at a certain time. The average intensity of the flame feature area and the position *X* of the flame front, that is, one input sample contains ten vectors.

The output value of the network is the combustion state index at the next moment. The burn index is defined on the trained Kohonen self-organizing neural network module. The characteristic parameters characterizing the combustion state of the furnace flame were first clustered by the Kohonen self-organizing neural network, fig. 5. The competitive response results representing the three different flames are clearly integrated into three different regions, namely the normal combustion zone, the abnormal combustion zone and the flameout zone. The nodes corresponding to the normal state of the coal-fired flame and the flame-off state of

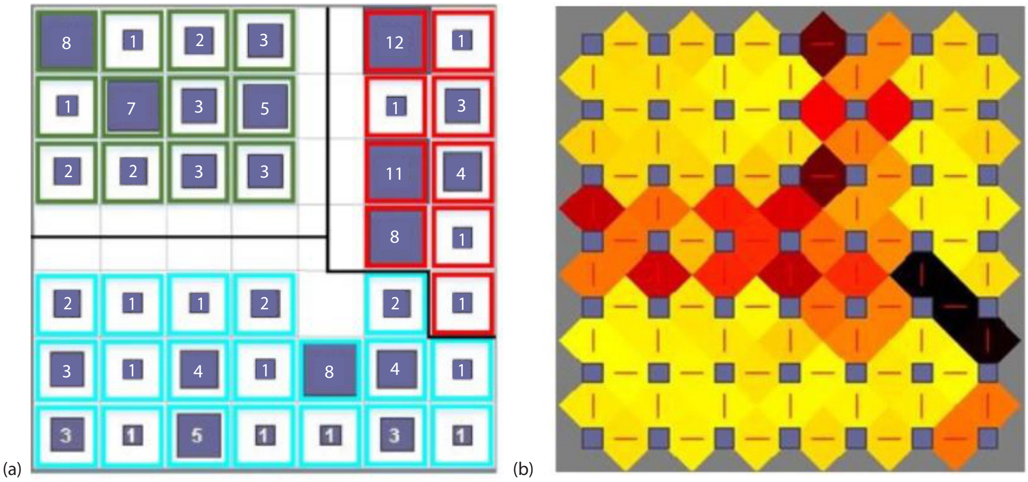

Figure 5. Kohonen neural network topology mapping of flame combustion index

the coal-fired flame are clearly integrated into two regions. Thus, for these two cluster regions, the respective cluster centers:

$$\left(i_{c\_\text{stable}}, j_{c\_\text{stable}} \text{ and } i_{c\_\text{distinct}}, j_{c\_\text{distinct}}\right)$$

can be obtained. Referring to the concept of membership in fuzzy mathematics, the definition of the combustion index:

$$e = \frac{\left(i\text{-}i_{c\_\text{distinct}}\right)^2 + \left(j\text{-}j_{c\_\text{distinct}}\right)^2}{\left(i\text{-}i_{c\_\text{stable}}\right)^2 + \left(j\text{-}j_{c\_\text{stable}}\right)^2 + \left(i\text{-}i_{c\_\text{distinct}}\right)^2 + \left(j\text{-}j_{c\_\text{distinct}}\right)^2} \tag{8}$$

where i, j are the co-ordinates of the winning node on the neural network topology map.

Thus, the combustion index is a value between 0.0 and 1.0, which characterizes the combustion state of the flame. Through training and testing, (0.0, 1.0) can be calibrated into three intervals (0, 0.2), (0.2, 0.6), and (0.6, 1.0), which correspond to three kinds of flameout, abnormal combustion and normal combustion. status. Which of the three intervals the combustion state index of the output at the next time falls indicates which combustion state the flame will be in? In the actual network calculation, it is one time every 10 minutes. That is to say, the input is the 10 characteristic values of the current time, and the output value is the flame burning state after 10 minutes. In this way, the identification and prediction of the flame combustion state is achieved.

Measurement system structure and test results

Measurement system structure

The structure of the measurement system is shown in fig. 6, consisting of an optical system, a CCD camera, and a computer processing unit. The optical system is an endoscopic optical periscope that is used to capture the image of the flame inside the furnace. The flame image is deflected by a prism and extracted by an optical fiber and projected on the target surface of the CCD camera. In order to make the optical system work safely in the furnace, a double-layered casing structure is adopted, which is cooled by cooling air, and the lens is cleaned by air-flow to prevent dust accumulation. The optical system is installed at the upper 30 m elevation of the boiler, and its field of view can effectively cover the entire furnace section obtain a complete flame combustion image of the whole furnace. The CCD camera captures the flame image at a rate of 25 frames per second and converts it into a video signal, which is then converted to a digital image by the image capture card. Then, the specially developed software is used to analyze and process the image information obtain the temperature field distribution and the feature quantity of various combustion conditions. Finally, using the artificial neural network model analysis, the full furnace combustion diagnosis results are obtained.

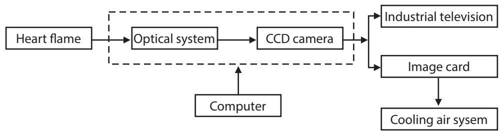

Figure 6. Measurement system structure

Temperature field measurement results

Using the aforementioned measurement system, a pilot study was carried out on 200 MW unit boiler of the power plant. Figure 7 is a corresponding isotherm and flame zone dividing line. The temperature range of the furnace is between 600 °C and 1450 °C. The flame of the four corners of the oil is better burned, the temperature of the flame edge changes sharply, the flame temperature changes continuously, and the distribution shows a certain vortex. Figure 7 uses the boundary detection and region segmentation methods to divide the flame into several relatively independent regions. The flames of the four oil guns were effectively segmented, and the burning conditions of the four oil guns were evaluated by calculating their centroids and average temperature.

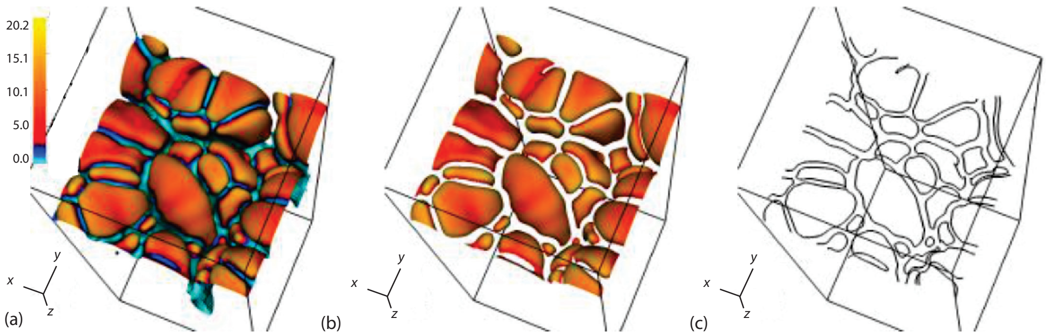

Figure 7. Corresponding isotherm and flame zone dividing line

Conclusion

Based on the theoretical analysis, this paper proposes a new method based on neural network model and using color CCD camera as sensor, using digital image processing technology to detect furnace flame temperature field and combustion diagnosis. A set of measuring systems designed according to the law was tested on a 200 MW unit boiler. The results show that the system is simple and practical, and can realize on-line detection of furnace flame temperature field and combustion diagnosis of boiler operation process, which has engineering application value.

References

[1] Song, J., *et al.*, A Globally Enhanced General Regression Neural Network for On-Line Multiple Emissions Prediction of Utility Boiler, *Knowledge-Based Systems*, *118* (2017), C, pp. 4-14

[2] Shaofei, W., Construction of Visual 3-D Fabric Reinforced Composite Thermal Performance Prediction System, *Thermal Science*, *23* (2019), 5, pp. 2857-2865
[3] Savchenko, A. V., Maximum-Likelihood Dissimilarities in Image Recognition with Deep Neural Networks, *Computer Optics*, *41* (2017), 3, pp. 422-430
[4] Tamer, A., *et al*., Image Mosaicing Based on Neural Networks, *International Journal of Computer Applications*, *136* (2016), 1, pp. 25-31
[5] Oko, E., *et al*., Neural Network Approach for Predicting Drum Pressure and Level in Coal-Fired Subcritical Power Plant, *Fuel*, *151* (2015), 26, pp. 139-145
[6] Lima, R. N., *et al*., Trend Modelling with Artificial Neural Networks, Case Study: Operating Zones Identification for Higher so 3 Incorporation in Cement Clinker, *Engineering Applications of Artificial Intelligence*, *54* (2016), C, pp. 17-25
[7] Shaofei, W., A Traffic Motion Object Extraction Algorithm, *International Journal of Bifurcation and Chaos*, *25* (2015), 14, 1540039
[8] Shin, H. C., *et al*., Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning, *IEEE Transactions on Medical Imaging*, *35* (2016), 5, pp. 1285-1298
[9] Cao, Y., *et al*., Spiking Deep Convolutional Neural Networks for Energy-Efficient Object Recognition, *International Journal of Computer Vision*, *113* (2015), 1, pp. 54-66

Paper submitted: October 12, 2019
Paper revised: November 19, 2019
Paper accepted: January 5, 2020