The Cooperation between Combustion Theory and Data Science Paves the Way to Advanced Combustion Diagnosis

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Abstract: ***This paper discusses how the development of data science influences that of combustion diagnosis technologies. In combustion, the energy is released from the chemical reaction between fuels and air. Flame is the glowing gaseous part of a fire. The image of the flame provides rich information on the combustion conditions such as fuel rich and fuel lean. Many features can be extracted from the flame images and the time-series analysis of the features can be directly employed to monitor the combustion conditions. The commonly used features include mean, standard deviation, third moment, Shannon entropy. The concept of attractorin nonlinear time-series analysis provides an effective framework to quantify the structure of the data embedded in high dimensional spaces. GARCH (Generalized Autoregressive Conditional Heteroskedasticity) is widely used to quantify the processes in which time-varying variances appear. The research on combustion and data mining mutually benefit and provide a basis for advanced combustion diagnosis.***

Keywords: combustion diagnosis; flame image; data mining; time-series; attractor; GARCH

1. Introduction

Combustion diagnosis is crucial important to the safety of thermal power plants and the environment protection [1-5]. With the development of high-speed camera, real time monitoring the combustion status inside the furnace of the plant has been realized. The turbulent nature of the flame results the difficulty of obtaining a mathematical model that can be used in industry level. However, flame sensing and flame image processing technologies offer a practical and effective way to diagnose combustion in industry equipment [1-3]. Nonlinear time-series analysis [6-8] methods based on attractor reconstruction and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model offers effective way to qualitatively diagnose the fluctuation of the time-series data of the feature extracted from flame images; this corresponds to the fluctuation of the combustion status.

2. Principle of Calculation of Flame Temperature

As to the wavelength of the light emitted from the flame in the furnaces in thermal power plants, it changesfrom 300nm to 1000nm and the flame temperature changes from 800K to 2600K. Under this circumstance, Wien's law [9] can be used to calculate the monochromatic exitance

$$E(\lambda,T)=\varepsilon_{\lambda}\frac{C_1}{\lambda^5}\exp(-\frac{C_2}{\lambda T}) \qquad (1)$$

where $E(\lambda,T)$ is the monochromatic radiant exitance, T the temperature, ε_{λ} the emissivity, λ the wavelength of , C_1 and C_2 the first and second Planck's constants respectively.

Two-color method is often used to get the flame temperature.In the flame color image, each pixel is associated with three values: R (red), G(green), B(blue). The red, green, and blue components are proportional to the radiant exitances of red, green, and blue lights.For a pixel im the flame image, the corresponding temperature is determined as:

$$T_{pixel}=C_2(\frac{1}{\lambda_G}-\frac{1}{\lambda_R})/\left(\ln\frac{R}{G}+\ln\left(\frac{\lambda_R}{\lambda_G}\right)^5\right) \qquad (2)$$

Where R and G are the values of the red and green channels of the pixel, λ_G and λ_R are the wavelengths of the green and red light respectively.

3. Background Removal in Flame Image Processing

In the process of flame image processing, an important point is to extract the flame region from the background. As to the edge detection, three edge detectors [10] are commonly used: Sobel, Robert, and Prewitt. Let $f(x,y)$ represent the pixel value at the point (x,y) in the digital image, the gradient the pixel value is determined as

$$\nabla f=\begin{bmatrix}G_x\\G_y\end{bmatrix}=\begin{bmatrix}\frac{\partial f}{\partial x}\\\frac{\partial f}{\partial y}\end{bmatrix} \qquad (3)$$

where G_x and G_y represent the gradient in the x and y directions respectively, and the absolute value of the gradient is:

Figure 1: Original flame image

Figure 2: Edge detection result

Figure 3: Binary image with flame region marked by white color

$$g = [G_x^2 + G_y^2]^{1/2} = [(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2]^{1/2} \quad (4)$$

If g is greater than a threshold value, the pixel is consider ed as an edge point. Fig.1 shows the original image, fig.2 s hows the result of the edge detection based on Sobel detect or, and in fig.3 it shows the flame region (marked by white pixels) after background (marked by black pixels) remova l.

4. Features of a Flame Image

Many features can be extracted from the flame image. They usually include mean value just represent the average intensity of the pixels in the flame region, the standard deviation measures the dispersion with respect to the mean value, the third moment is also called skewness which measures the asymmetry leaning to the left or the right side.

Shannon entropy [10] is a quantitative measure of the uncertainty of a signal, and it is defined as:

$$I = -\sum_i p_i \cdot \log_2 p_i \quad (5)$$

where I is the Shannon entropy, p_i is the probability of the i thevent.

5. Attractor Reconstruction from Time Series Data

Usually, time-series is a sequence of data representing some quantity such as temperature, pressure, concentration, and etc. Takens' theorem [8] has been widely used to get the attractor from time-series data. It depends on a method called delay reconstruction. In m-dimensional space, the delay reconstruction is formed by the vectors $\mathbf{S_n}$ that is shown below

$$\mathbf{S_n} = \left\{ s_{n-(m-1)\tau}, s_{n-(m-2)\tau}, s_{n-(m-3)\tau} \cdots, s_{n-2\tau}, s_{n-\tau}, s_n \right\} \quad (6)$$

where s is the original time-series data. The set of the data reconstructed in the phase space is named attractor. There are many types of attractors [8] such as fixed point, limit circle, and fractal.

A fix-point-like attractor means the data in the phase space finally settles down at a point. As to a limit-circle-like attractor, all data gather on a limit circle in the phase space. In a fractal attractor, the self-similarity appears. For a time-series data of the feature of the flame image, the attractor can be reconstructed, and it represents the characteristic nature of the combustion process.

6. GARCH Model

Regarding an autoregressive process, there exists a connection between the past observations and present ones. GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model describes the process in which time-varying variance [8] dominates, and conditional heteroskedasticity means that the current observations depend on the immediate past ones.

For a GARCH(P,Q) model for the conditional variance of innovations is the following:

$$\sigma_t^2 = \kappa + G_1\sigma_{t-1}^2 + G_2\sigma_{t-2}^2 + \cdots + G_P\sigma_{t-P}^2 + A_1\varepsilon_{t-1}^2 + A_2\varepsilon_{t-2}^2 + \cdots + A_Q\varepsilon_{t-Q}^2 \quad (7)$$

where σ^2 is the variance and ε is the error term.And the constraints below need to be satisfied :

$$\kappa > 0 \quad (8)$$

$$G_i \geq 0, \quad i = 1, 2, ..., P \quad (9)$$

$$A_j \geq 0, \quad j = 1, 2, ..., Q \quad (10)$$

$$\sum_{i=1}^{P} G_i + \sum_{j=1}^{Q} A_j < 1 \quad (11)$$

An important point to generate a GARCH process is below:

$$\varepsilon_t = \sigma_t W_t \quad (12)$$

where W_t represents white noise.

The time-series data of the features can be tested if it is governed by a GARCH process.

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