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 attractor 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 changes from 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

$$E(\lambda, T) = \varepsilon\frac{C_1}{\lambda^5} \exp\left(-\frac{C_2}{\lambda T}\right)$$  \hspace{1cm} (1)

where $E(\lambda, T)$ is the monochromatic radiant exitance, $T$ is the temperature, $\varepsilon$ is the emissivity, $\lambda$ is 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 in the flame image, the corresponding temperature is determined as:

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

Where R and G are the values of the red and green channels of the pixel, $\lambda_G$ and $\lambda_R$ 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 of the pixel value is determined as

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$  \hspace{1cm} (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:

$$\|\nabla f\| = \sqrt{G_x^2 + G_y^2}$$
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.

\[
\sigma_i^2 = \kappa + G_1 \sigma_{i-1}^2 + G_2 \sigma_{i-2}^2 + \cdots + G_P \sigma_{i-P}^2 + A_1 \varepsilon_{i-1}^2 + A_2 \varepsilon_{i-2}^2 + \cdots + A_Q \varepsilon_{i-Q}^2 \tag{7}
\]

where \( \sigma^2 \) is the variance and \( \varepsilon \) is the error term. And the constraints below need to be satisfied:

\[
\begin{align*}
\kappa &> 0 \\
G_i &\geq 0, \quad i = 1, 2, \ldots, P \\
A_j &\geq 0, \quad j = 1, 2, \ldots, Q \\
\sum_{i=1}^{P} G_i + \sum_{j=1}^{Q} A_j &< 1
\end{align*}
\]

An important point to generate a GARCH process is below:

\[
\varepsilon_i = \sigma_i W_i \tag{12}
\]

where \( W_i \) represents white noise.

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


