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Burning state recognition of rotary kiln using ELMs with heterogeneous features

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ABSTRACT

Image based burning state recognition plays an important role in sintering process control of rotary kiln. Although many efforts on dealing with this problem have been made over the past years, the recognition performance cannot be satisfactory due to the disturbance from smoke and dust inside the kiln. This work aims to develop a reliable burning state recognition system using extreme learning machines with heterogeneous features. The recorded flame images are firstly represented by various low-level features, which characterize the distribution of the temperature field and the flame color, the local and global configurations. To learn the merits of our proposed flame image-based burning state recognition system, four learner models (ELM, MLP, PNN and SVM) are examined by a typical flame image database with 482 images. Simulation results demonstrate that the heterogeneous features based ELM classifiers outperform other classifiers in terms of both recognition accuracy and computational complexity.

1. Introduction

Rotary kiln, as a large-scale sintering facility, is widely used in metallurgical, cement, chemical, and environment protection industries. The main control objective of the rotary kiln sintering process is to achieve consistent product quality, which is often referred to as the key performance index. However, practically, the measurement of the product quality index is done by manual sampling with 1-h period. Therefore, indirect control is employed to replace online control, i.e. keeping key process parameters that can be measured online and are closely related to the product quality index into their preset ranges means satisfied product quality index. Based on the analysis of rotary kiln mechanism process, the fact that burning zone temperature directly determines the characteristics of the clinker is widely acknowledged. Thus, the accurate measurement for such temperature is the most critical issue for the rotary kiln sintering control process [1–3]. However, due to the harsh environment inside the kiln, the accurate measurement through thermocouple is still a challenging task. Recently, we have developed and implemented a hybrid control system in No. 3 rotary kiln at Shanxi Aluminum Corp. [4]. In such system, burning state is recognized based on the clustering of temperatures from the non-contact colorimetric measuring device.

Because of the rich and reliable visual information, for operators, burning zone flame image is considered to be more reliable than the burning zone temperature to estimate the burning state. Flame image-based state recognition has already been studied in the past, where a flame image is first segmented into regions of interest (ROIs), features for the representation of the color and configuration characteristics of these regions are then extracted, burning state recognition is performed based on the features extracted [5–7]. However, due to the poor image quality caused by smoke and dust inside the kiln, accurate segmentation of ROIs is quite challenging and therefore unreliable. This will in turn result in inaccurate feature extraction and poor state recognition. To avoid the above problems, we have tried to extract features to represent the color and configuration characteristics of ROIs of flame image without segmentation, with the goal of improving the burning state recognition.

From operators point of view, more discriminable ROIs will facilitate the subsequent feature extraction and burning state recognition. Motivated by the knowledge that flame and material zones are with distinct texture characteristics, Gabor filter is employed as a pre-processing step to discriminate them [8]. Practically, its parameters are often set by trial and error. However, we believe most of a filter bank offer little improvement to (or even reduce) the discriminative power due to the peaking phenomenon [9]. Hence, we propose to incorporate Mahalanobis

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measure [10] and forward selection technique [9] to automatically generate a compact Gabor filter bank to enhance the separability of ROIs to facilitate the sequel.

Flame color indicates the combustion region and the distribution of the temperature field, and hence exhibits an intuitive impression for the burning state. Appropriate flame region with similar color corresponds normal burning state. Unlike other flame image analysis methods that track the turbulent flame in the image space to extract features to represent the flame color, the multivariate image analysis (MIA) technique [11] shows its efficiency to feature the flame color without the difficult locating flame step. MIA lies in projecting image pixels with similar color in a common region of the score space independently of their spatial location, and retrieving the locations of pixels with similar color in the image space after detecting feature in the score space. Such extracted feature will be used to represent the flame color.

The configuration of ROIs characterizes the heat source, disturbance from smoke and dust, and clinker sintering status. Especially, the configuration of the flame zone and the height of the material zone are the key factors to recognize the burning state [5,6]. Flame zone with good circularity and appropriate material height mean normal burning state. Due to the difficult segmentation of ROIs, instead, global features are firstly extracted to represent the global configuration of the flame image. Eigen-flame images are obtained using principal component analysis (PCA), and global features are then produced by correlating each flame image with the eigen-flame images to represent the global configuration. Unlike traditional selection criterion for eigen-images [12], a new selection procedure is used, with the goal of selecting global features that possess the maximum discriminative power.

Generally, local configuration is considered to contain more valuable details to complement the global configuration. Scale invariant feature transform (SIFT) operator [13] is hence employed to extract key points of flame image to avoid the segmentation. The dimension of a SIFT descriptor is 1×128. Exploring research in image and text retrieval, "bag of visual words" (BoVW) [14] and term frequency-inverse document frequency weight [15] are applied to vector quantize the descriptors into clusters and form a visual word-image table to reduce feature representation dimension. For such table, latent semantic analysis (LSA) [16] is used to map such visual word-image space to a latent semantic space by taking advantage of some implicit higher-order structure in associations of visual words with images to mitigate potential zero-frequency problem and reduce feature dimension further [17]. Now, semantic vector as local feature conceptually represents the local configuration. Previously, semantics are explicitly assumed to have same saliency. In our work, a new semantic selection procedure is introduced in order to consider the saliency of semantics to select local features with maximum discriminative power.

To imitate the fact that the integration of multi-feature is used to estimate the final burning state, the above individual features are concatenate and normalized, and a single-hidden-layer feed forward neural networks (SLFNs) classifier with extreme learning machine (ELM) algorithm [18] is employed to recognize the burning state. Different from conventional learning algorithms for neural networks, with randomly chosen input weights and hidden bias and calculated output weights, ELM not only trains much faster with higher generalization ability, but also overcomes many issues faced by gradient-based algorithms such as stopping criteria, learning rate, learning epochs, and local minima. Many types of hidden nodes including additive/RBF hidden nodes, multiplicative nodes, and non-neural alike nodes, can be used as long as they are piecewise nonlinear. Readers may refer to a recent survey paper for more details on ELM [19]. In ELM, since different hidden node parameters correspond to different classification performance, the selection of the hidden node number is the most critical issue. Recently, due to the universal approximation capability, the minimum training error and weight norm, diverse modification for ELM has been successfully applied to many classification problems [20] but has never been used in flame image recognition before. The advantages of our new flame image-based burning state recognition method are fourfold. Firstly, our new method is computationally more efficient and more accurate and robust than the image segmentation-based and temperature-based methods. Secondly, MIA is effective to feature the flame color to avoid the difficult flame tracking. Thirdly, eigen-flame image-based method is feasible to feature the global configuration to avoid the difficult segmentation. Fourthly, without segmentation, local configuration is effectively featured by semantic vector. Numerous experimental studies show that, with feasible ELM classifier, our new method outperforms the image segmentation-based methods and temperature-based method. As we can expect, more consistent product quality index can be achieved if the new burning state recognition method is incorporated into our previously developed hybrid control system.

The rest of the paper is organized as follows. The rotary kiln sintering process and weaknesses of previous burning state recognition methods are presented in Section 2. Section 3 gives our new flame image multi-feature-based burning state recognition method. Experimental studies, conclusions and future work are given in Sections 4 and 5 respectively.

2. Rotary kiln sintering process and previous burning state recognition methods

2.1. Rotary kiln sintering process

A schematic diagram of the rotary kiln sintering process is shown in Fig. 1, where raw material slurry is sprayed into the rotary kiln the upper end, i.e. kiln tail. At the lower end, i.e. kiln head, coal powders from the coal feeder and primary air from the air blower are mixed into a bi-phase fuel flow and then are sprayed into the kiln head hood and combust with secondary air from the cooler. The heated gas is brought to the kiln tail by the induced draft fan, while the material moves to the kiln head by the rotation of kiln and its gravity, in counter direction of the gas flow. After the material passes through drying zone, pre-heating zone, decomposing zone, burning zone, and cooling zone in sequence, the final product of the sintering process of rotary kiln, namely clinker, is generated and is fed downstream for further processing [21]. Taking alumina sintering process for instance, during burning zone, with 1200–1300 °C, the following chemical reaction arises [21]:

$$Na_2O \cdot Al_2O_3 \cdot 2S_iO_2 + 4CaO \rightarrow Na_2O \cdot Al_2O_3 + 2(2CaO \cdot S_iO_2) \qquad (1)$$

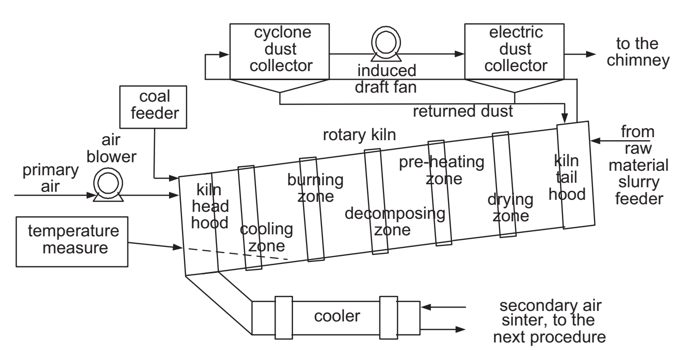

Fig. 1. Schematic diagram of rotary kiln sintering process.