Quantitative Analysis of Mineral Composition of Iron Ore Sinter
Based on Comprehensive Image Processing Techniques

Hong-wei GUO,1,2)* Bu-xin SU,2) Zhen-long BAI,3) Jian-liang ZHANG2) Xin-yu LI2) and Feng LIU2)
1) Shangang School of Iron and Steel, Soochow University, Suzhou, 215021 China.
2) School of Metallurgical and Ecological Engineering, University of Science & Technology Beijing, Beijing, 100083 China.
3) School of Automation and Electrical Engineering, University of Science & Technology Beijing, Beijing, 100083 China.

To acquire the mineral composition of iron ore sinter, the research work until now mainly focuses on two aspects which are traditional manual method often called Point Counting Method and Image Processing Method respectively. Point Counting Method is of high labor intensity and of low efficiency compared with Image Processing Method. Meanwhile, existing Image Processing Method always encounters low accuracy when it is applied to analyze the sinter with special microstructure such as large pores. This paper presents an improved method based on modified gray-level images and extracted texture images with knowledge base rules, producing the final images more suitable for computer to deal with. The experimental results demonstrate that this improved technique is valid for quantifying the mineral composition of sinter and it has a higher-level accuracy of recognition than existing image processing methods do.

KEY WORDS: sinter; quantitative analysis of the mineral composition; digital image processing.

1. Introduction

Iron ore sinter is one of important ferrous burdens charged into blast furnace. Stability of blast furnace operation to some extent depends upon the properties of sinter, especially when it occupies a very large fraction. Generally speaking, sinter quality is determined by the mineral composition and microstructure. The sintering theory of iron ore fines and practical production show that the bonding phases present during sintering process make iron ore fines bond together. It is worth noting that among these different bonding phases, complex Silico-Ferrites of Calcium and Aluminium (SFCA) is the best. Both the amount of SFCA and its morphology play an important role in influencing key sinter-quality parameters such as mechanical strength and reducibility.1–5) Therefore, it is urgent to find an effective way to qualitatively and quantitatively analyze mineral composition of sinter with a certain level of accuracy so as to optimize the ore-blending and sintering process. However, traditional Point Counting Method is laborious,6) besides, the accuracy of experimental results is always affected by the experience and skill of the operator.

Digital image processing is a new kind of analysis technique by using a computer, and now it has been applied widely in many fields. For mineralogical analysis, several famous systems or methods have already been developed to quantitatively measure mineral composition. Sato et al.9) lead this field in 1982, correlating sinter mineral composition to sinter quality for the first time. IRSID (Institute of Research of French Steel Industry) and the School of Mines of Paris10) devised a system based on operational morphological operation in 1983 where Jeulin introduced a method to calculate the phase area through morphological operations such as image corrosion, image dilation, and border detection. Another system is in 1985, which was developed by Nippon Corporation and Dr. Yanaka of the University of Tokyo based on pixel statistics.8) This method determined the phase area by counting the pixels of the phase in an image. In recent years, a set of intelligent recognition and quantification system was developed by Professor Bai Chenguang of Chongqing University. In their system, the calculation of mineral composition was conducted by applying genetic algorithm and the extraction of image texture feature was introduced to do mineralogical phase recognition. However, sometimes the large pores existing in the sinter microstructure render this system produce errors inevitably.10–12) To solve this problem, this paper is aimed at applying comprehensive Image Processing Method not only to quantify the mineral composition of sinter but also work out the proportion of the pores.

To process original micrographs, several processing techniques are applied to acquire proper processed images. It can be classified into two categories according to references:7–11) 1) both mineral composition recognition and quantification are realized according to characteristics of the distribution of gray level derived from the difference of reflectivity for different minerals; 2) mineral composition recognition is carried out by making use of texture features. However, the first method might fail when two kinds of minerals with

* Corresponding author: E-mail: ghwustb@gmail.com
DOI: http://dx.doi.org/10.2355/isijinternational.54.1222
similar reflectivity are identified. For example, in some cases, the difference of reflectivity for magnetite and hematite is relatively small, merely 1–2%. As for the second method, its application could be limited resulting from insignificantly different texture features such as the similarity of texture features for calcium ferrite, magnetite and hematite. Therefore, to improve existing methods, this paper applied a more advanced method to deal with the problems of composition recognition and quantification for minerals with a high-level accuracy.

2. Experimental

2.1. Sinter Sample Preparation

The composition of iron ore used for sinter sample preparation in this study was given in Table 1. The detailed sample preparation procedures were as follows: Firstly, sample-making device was used to produce two green cake samples (one was duplicated sample) for each kind of iron ore fines with a specific chemical composition mixed with analytically pure CaO. In the sample-making process, the mixture with the average particle size of iron ore fines 0.074 μm was pressed into green cake samples with a dimension of 20 mm (diameter) × 5 (height) mm. The second step was to heat these green samples in a muffle furnace. Sintering condition was following: 1) heating rate was 15 K/min before 1 173 K and 5 K/min after 1 173 K respectively. 2) peak temperature was set as 1 553 K and held at this temperature for 5 minutes, and then these samples were cooled down with the furnace. 3) the experimental atmosphere was air. Finally, these sintered cake samples were ground and polished by using sample-grinding device consisted of grinding prototype, polishing machine, glass plate, quartz sand and vanadium pentoxide aqueous solution. These polished samples were hot mounted by using epoxy resin and observed with the help of a polarized microscope to get original micrographs. The field of view was ×500 and the number of detected points was 500. Moreover, one hundred of pictures were taken for every sample using a digital camera. The size of these pictures was 3 456×2 304, and 2.5 M space was needed for every picture. Finally, these pictures were saved as JPEG.

2.2. Procedures of Image Processing

The original micrographs in this study were processed mainly in two aspects: 1) the distribution of image gray level: a given micrograph would demonstrate particular distribution characteristics of gray level due to different reflective abilities of different kinds of minerals for incident light, e.g. uniform degree of the distribution of gray level, the peak value of histograms of image, etc.; 2) the texture feature of image: a given micrograph would present particular texture features because different minerals have different crystalline structures as well as different crystallization processes, e.g. the coarseness degree, the clarity, the complexity and the similarity in different directions and so on.

Compared with conventional image processing techniques, the comprehensive image processing involving contrast enhancement, histogram equalization, and threshold operation aims at amplifying the difference of gray values in an image. The extracted characteristics of gray level distribution is suitable for primary composition recognition. Besides, based on above-mentioned processed images, further processing are conducted, such as edge location and texture feature extraction. In this research, Canny operator

| Table 1. Chemical composition of iron ore powders. | wt/% |
|---|---|---|---|---|---|---|---|
| Cord | TFe | FeO | CaO | SiO₂ | MgO | Al₂O₃ | Ig |
| A  | 61.7 | 0.40 | 0.32 | 4.11 | 0.10 | 2.61 | 3.99 |
| B  | 61.7 | 0.12 | 0.22 | 9.10 | 0.06 | 1.25 | 4.35 |
| C  | 61.2 | 0.31 | 0.28 | 9.52 | 0.05 | 2.88 | 5.67 |
| D  | 65.6 | 24.65 | 0.50 | 1.46 | 2.37 | 0.39 | 0.05 |
| E  | 61.7 | 0.26 | 1.66 | 5.67 | 0.30 | 1.83 | 1.45 |
| F  | 66.1 | 25.81 | 0.95 | 2.70 | 0.33 | 0.74 | 1.56 |
| G  | 62.0 | 25.45 | 2.45 | 2.93 | 1.08 | 0.82 | 0.25 |

Fig. 1. Overall image processing flow chart.
and Gabor Filter methods were applied for these two goals. At last, the images after extracting texture feature were combined with previously preliminary processed images, i.e., only the distribution characteristics of gray level were considered, and then all the images were used to recognize mineral composition of sinter and acquire relatively accurate quantitative information about minerals under some certain rules and algorithms established in this paper. Figure 1 shows the flowchart of the overall image processing.

2.2.1. Acquisition of the Original Micrograph

Figure 2(a) is the original image of the sinter sample C, showing: 1) the pores existed but not very obvious; 2) the bonding phase mainly was SCFA with a characteristic “platy” morphology; 3) the amount of SFCA is relatively a little lot.

2.2.2. Contrast Enhancement and Histogram Equalization

To reduce negative effects of the noises which might influence the accuracy of the experimental results the original micrograph had and provide more suitable images for computer to handle, contrast enhancement and histogram equalization were applied.

Figures 2(b) and 2(c) show the processed images acquired by enhancing contrast and doing histogram equalization respectively for the original micrograph of sample C.

2.2.3. Threshold Operation

Threshold operation is a special type of quantization that separates the pixel values in two classes depending upon a given threshold value. Figure 2(d) shows the threshold operation for the processed micrograph of sample C.

Histogram equalization and threshold operation increase the robustness of the following texture feature extraction. If original micrographs are directly used to extract texture feature, the dark area and the area with non-uniform brightness in the original micrograph will be poorly distinguished.

2.2.4. Canny Operator and Gabor Filter Methods

Texture feature extraction is a key procedure to accurately

![Fig. 2. Original micrograph and Processed images of the sinter sample C.](image-url)
describe image texture and classify different kinds of minerals. In order to extract texture feature, edge image is prerequisite. Canny operator was used to obtain the edge image, which was processed with the image after threshold operation.

Canny operator: employs a set of relatively large, oriented filters at multiple image resolutions and merges the individual results into a common edge map. This operator tries to satisfy the following three criteria: 1) excellent detection ability for edge; 2) accurate localization for edge; 3) single response. The Canny operator substantially is a gradient method (based on the first order derivative of Gaussian function), but it uses the zero crossings of second derivatives for precise edge localization. In the case of “step edges”, the directional derivative of Gauss function and the convolution of an image are calculated by applying the symmetry and factorability of the two-dimensional Gauss function. In this paper, the first order derivative of Gaussian function is chosen as suboptimum operator in the case of step edges.

This paper used Gabor filter methods for texture feature extraction. First of all, a group of Gabor filters were designed to filter the texture of image. It is worthy to note that each Gabor filter only allows the texture which has a particular frequency to pass smoothly, and the other textures cannot get through. Thus different texture features were extracted from the outputs of these Gabor filters. Second, the pixel value at every point in texture image was acquired by using Gaussian filter at each sampling center point to get all the pixel values for texture image. Then stretch grayscale of texture image to obtain Fig. 2(f).

2.2.5. Composition Calculation

Assume that the gray level of every mineral in sinter obeys normal distribution in a specific range:

\[ F_i \sim N(\mu, \sigma^2) \]

In the expression (3), \( F_i \) is the gray level distribution of mineral \( i \), and \( \mu, \sigma \) are the mean and variance respectively. The values of \( \mu, \sigma^2 \) are computed as following formulas:

\[ \mu = \mathbb{E}(F) = \sum_{i=m_i} F_i \times \phi(i) \]

\[ \sigma^2 = \mathbb{D}(F) = \sum_{i=m_i} F_i^2 \times \phi(i) \]

\[ \mathbb{E}(F) = (\mathbb{E}(F))^2 - \mathbb{D}(F) \]

In the formulas (4) and (6), \( m_{\text{max}} \) and \( m_{\text{min}} \) are the maximum and minimum gray level of corresponding mineral. In addition, \( \phi(i) \) is the statistical frequency of \( F_i \) of mineral \( i \). The statistical calculation was conducted on the treated samples to obtain mean and variance of different minerals.

In this paper, seven hundreds of pictures derived from texture feature extraction and contrast enhancement for every specimen were divided into two parts: five hundreds of these pictures acted as training samples and the remaining as testing samples. These training samples were used to acquire statistical frequency of gray level. By using above-described expressions, the distribution curve of gray level of a certain mineral was obtained.

However, region crossing phenomena might occur for two gray level distribution curves of two different minerals. In order to obtain superposition gray level distribution of two kinds of minerals, it is necessary to consider two situations:

1) As shown in Fig. 3(a), there is a weak overlap between the curves of distribution of gray level of two minerals. Thus, two peaks occur after summing.

2) As shown in Fig. 3(b), there is an extensive overlap between the curves of distribution of gray level of two minerals. Thus, single peak occurs after summing.

![Fig. 3. Superposition distribution for 2 normal distribution curve. (Online version in color.)](image-url)
In this paper, above two situations were treated in separate ways. For Fig. 3(a), gray classification technique based on contrast enhancement images was used to distinguish two minerals. However, for Fig. 3(b), instead of gray classification, Gabor texture feature extraction was applied to distinguish two minerals.

The necessary procedures for gray classification were following (these operations were conducted on testing samples): Firstly, the mineral set (the number of minerals is finite) was denoted by \{S_{ni}\}; Secondly, for a given point \((x, y)\), the gray level was transformed into \(g(x, y)\) after contrast enhancement; At last, by putting resultant \(g(x, y)\)'s into formula (3), the distribution curve of Si is thus obtained. Through setting different threshold values, different minerals were distinguished and quantified.

When extensive overlap occurred between two distribution curves, to distinguish these two kinds of minerals in the case of the failure of gray classification, Gabor texture feature images were introduced to get threshold values capable of recognizing minerals.

The detailed algorithm was as follows:

The first step: classified the points \((x, y)\) into four constituents:

1) Pores or cracks
2) Silicates
3) Magnetite or calcium ferrite
4) Hematite

The second step: distinguished magnetite and calcium ferrite by applying Gabor texture feature extraction.

The third step: refined silicates by detecting whether silicates surrounding pores and recounting them as pores.

According to Figs. 2(f) and 2(b), different minerals are classified based on the following rule (called knowledge base rules):

**Definition:**

\[
\text{value1} = \text{the pixel value at one point in Fig. 2(f)}; \\
\text{value2} = \text{the pixel value at one point in Fig. 2(b)}. \\
\text{Rule: (\text{//} \text{means “refer to”})}
\]

\[
\begin{align*}
&\text{if (value1 > A1 && value2 B2) // Hematite} \\
&\text{else if (value1 > A2 && value2 <= A1 && value2 >= B1) // Magnetite} \\
&\text{else if (value1 > A3 && value2 >= B1) // SFCA} \\
&\text{else if (value1 < A3 && value2 < B2) // pores} \\
&\text{else if (value1 > A3 && value1 <= A2 && value2 < B1) // Silicates}
\end{align*}
\]

A1, A2, A3 and B1, B2 are all gray level threshold values related to the different minerals in sinter. The primary determination of these threshold values was realized based on training samples and then was tested and revised according to testing samples. This paper set the final A1, A2, A3 and B1, B2 as 210, 178, 120 and 46, 156, respectively.

After calculation, the proportion of all minerals including pores was: magnetite 39.1%, SFCA 34.8%, silicate 10.1%, pores 16%. It is noteworthy that the proportion of magnetite could be ignored because the specimens came from experiment room not from practical production site.

### 3. Results and Discussion

#### 3.1. Comparison with Point Counting Method

In this research, seven kinds of samples which are sintered under the same sintering conditions that are \(T=1553\ K, CaO/SiO_2=2.0\) (weight percentage ratio) are all conducting observations under microscope and image processing to identify and quantify the mineral composition. Table 2 shows the main mineral composition and their proportions of these sinter samples by using Point Counting Method and image processing analysis respectively.

Table 2 shows the production ability of SFCA of these seven kinds of iron ore fines can be arranged in the order of the amount of SFCA: \(C>B>G>F>E>A>D\). Besides, the amounts of pores for different sinter samples are also significantly different. By comparing with Point Counting Method, the results for the amount of pores are reliable.

#### 3.2. Comparison with Gray Classification

Reference 7 applied gray classification to acquire the gray level distribution so as to identify and quantify mineral compositions. The differences of gray level for different minerals are as follows: the smallest difference is 9.5 resulting from calcium silicate and pores; the difference between magnetite and calcium ferrite is 11.6; the difference between magnetite and hematite is 16.7. To distinguish different minerals, this paper set gray level between 16 and 256. The processed image obtained from gray classification is shown in Fig. 4 which gave the following calculation result: hematite 52.4%, SFCA 7.6%, Silicate 24.8%, pores 15.2%. In Fig. 5, comprehensive image processing method was compared with gray classification.

Figure 5 shows that gray classification fails to recognize silicate ferrite and hematite. Besides, the quantitative results for SFCA obtained from these two methods vary widely. For

| Table 2. Mineral composition and the proportion of pores for seven sinter samples in two quantitative methods. |
|---------------------------------------------------------------|
| Iron ore fines | Manual quantitative method | Comprehensive Image Processing |
| Magnetite | Hematite | SFCA | Pores | Magnetite | Hematite | SFCA | Pores |
| A | 0 | 50 | 12 | 23 | 0 | 47.5 | 12.8 | 23.4 |
| B | 0 | 33 | 36 | 18 | 0 | 40.8 | 34.3 | 21.2 |
| C | 0 | 24 | 45 | 17 | 0.5 | 25.4 | 43.5 | 16.7 |
| D | 48 | 14 | 5 | 15 | 47.1 | 13.5 | 8.4 | 14.0 |
| E | 5 | 56 | 12 | 36 | 4.9 | 52.6 | 11.2 | 36.4 |
| F | 0 | 42 | 14 | 32 | 0 | 42.8 | 12.4 | 30.2 |
| G | 15 | 16 | 30 | 35 | 14.4 | 17.0 | 30.5 | 31.5 |
gray classification, the amount of SFCA is 7.6%, instead of 34.8% by using comprehensive image processing method. Because of the low resolution of gray classification, the pinnae structure was recognized as hematite and silicates. In contrast, comprehensive image processing method considered not only characteristics of gray level distribution but texture features of different minerals so as to capture more accurate distribution information.

4. Conclusions

This paper applies digital image processing techniques to quantify the mineral composition. Start with the original micrograph, and do contrast enhancement, histogram equalization and threshold operation. Then extract texture feature by using Canny operator and Gabor filter methods and classify different minerals based on knowledge base rules. The experimental results show that the present technique is valid for quantifying the mineral composition of sinter and it has a high-level accuracy of recognition compared with gray classification.

Acknowledgement

This work is supported by National Natural Science Foundation of China (No. 51204013) and Youth Education Talent Plan in USTB (YETP0350) and National Key Technology R&D Program in the 12th Five Year Plan of China (NO.2011BAC01B02).

REFERENCES

1) J. M. F. Clout and J. R. Manue: Powder Technol., 130 (2003), 393.
2) L. X. Yang and E. Matthews, ISIJ Int., 37 (1997), 854.
3) M. I. Pownceby and J. M. F. Clout: Miner. Process. Extract., 112 (2003), 44.
4) N. Y. Scarlett, M. I. Pownceby and I Madsen: Metall. Mater. Trans. B, 35 (2004), 929.
5) S. L. Wu, Y. Liu and J. X. Du: J. Univ. Sci. Technol. Beijing, 24 (2002), 254.
6) L. G. Zhou: Mineralogy Process, Metallurgy Industry Press, Beijing, (2007).
7) D. Jeulin: Ironmaking Steelmaking, 10 (1983), 145.
8) Y. Shibuya, H. Yanaka and K. Takemoto: Trans. Iron Steel Inst. Jpn., 25 (1985), 257.
9) K. Sato, S. Suzuki, Y. Sawamura and K. Ono: Tetsu-to-Hagané, 68 (1982), 2215.
10) X. W. Lv, C. G. Bai and G. B. Qiu: ISIJ Int., 49 (2009), 703.
11) X. W. Lv, C. G. Bai and G. B. Qiu: ISIJ Int., 49 (2009), 709.
12) X. W. Lv, C. G. Bai and G. B. Qiu: ISIJ Int., 48 (2008), 186.
13) W. Burger and M. J. Burge: Principles of Digital Image Processing, Fundamental Techniques, Springer, Germany, (2009), 144.