

A simple methodology for identifying hematite grains under polarized reflected light microscopy

Otávio da Fonseca Martins Gomes
CETEM – Centre for Mineral Technology
Rio de Janeiro, Brazil
ogomes@gmail.com

Sidnei Paciornik and Julio Cesar Alvarez Iglesias
Department of Materials Engineering
PUC-Rio – Catholic University of Rio de Janeiro
Rio de Janeiro, Brazil
sidnei@puc-rio.br, julioc.alvarez@gmail.com

Abstract— The identification of hematite grains is an intermediate task that aids the texture characterization of iron ores, a key step in quality control. The present paper proposes a simple methodology for identifying hematite grains in images obtained by reflected light microscopy, with promising results. An automatic image processing routine segments hematite grains imaged under two polarizer/analyzer angles.

Keywords—iron ore, texture, ore characterization, reflected light microscopy, polarized light

I. INTRODUCTION

The growing use of iron ore and its by-products in consumer products manufacture evidences the importance of this industry for the national and global economy. On the other hand, the quality of available iron ores has been decreasing over the years. Therefore, mining companies strive for improvements in their products in order to maintain and upgrade their performance in the market.

The traditional trading of iron ores is based on chemical specifications and particle size distribution. However, recent characterization studies that bring additional information have become important. In fact, porosity, quantitative mineralogy, fabric analysis (spatial distribution of different minerals within the particles) and texture analysis (spatial distribution of different grains within a mineral) can contribute to the determination of the iron ores downstream beneficiation operations and subsequent steelmaking process, allowing improvements on both new and existing processes [1,2].

Qualitative characterization of iron ores is typically performed by visual examination under the reflected light microscope (RLM). The most common iron-bearing minerals (hematite, magnetite and goethite) can be visually identified on RLM through their distinct reflectances [3].

Automatic image analysis systems are capable of identifying hematite, magnetite and goethite by their colors on suitable RLM images. In recent years, some methodologies [4–7] were developed for performing

mineralogical characterization of iron ores through image analysis systems.

The Brazilian iron ores have a simple mineralogy, generally involving hematite, magnetite, goethite and some gangue minerals, mainly quartz. Practically all of them are of the hematite prevailing type. Nevertheless, they present very diverse microstructures. Different characters of hematite grains, such as lamellar, granular and recrystallized, are found.

Hematite is a strongly anisotropic mineral. It presents bireflectance [3], i.e. its reflectance and consequently its brightness in images change with different crystal lattice orientations under plane polarized light. This brightness variation is subtle, but it is perceptible to a trained human eye on RLM.

On the other hand, the combined use of a polarizer and an analyzer in RLM promotes brightness and color variations due to anisotropy [8]. This approach can be used to obtain images that present sufficient contrast to differentiate grains. Pirard et al. [9] developed an image processing methodology to determinate hematite grain boundaries in which a set of seven images per field is acquired rotating the polarizer by short steps.

The present paper proposes a simple methodology for perform an automatic identification of hematite grains in images obtained on RLM. This methodology uses an image processing routine composed of classical techniques to segment hematite grains imaged under two polarizer/analyzer angles, combined with an image obtained without the analyzer.

II. METHODOLOGY

A. Image acquisition

A motorized and computer controlled RLM with a digital camera (RGB, 24 bits, 1300 x 1030 pixels) was employed to acquire images from polished cross-sections of iron ore samples. Three images per field (sample location) were acquired:

- a 24 bit RGB *mineralogical image* obtained without the analyzer (Figure 1);

- a 24 bit RGB *crystallographic image* obtained with the polarizer rotated about 30° from the crossed nicols arrangement (Figure 2);
- a 24 bit RGB *crystallographic image* obtained with polarizer rotated about -30° from the crossed nicols arrangement (Figure 3).

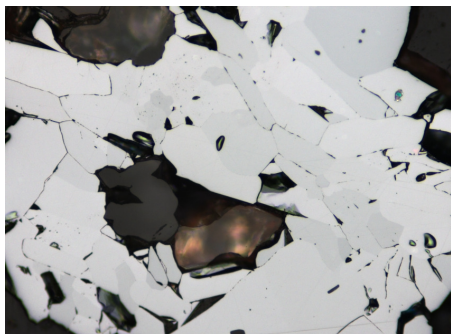


Figure 1. Mineralogical image: image obtained on RLM without the analyzer.

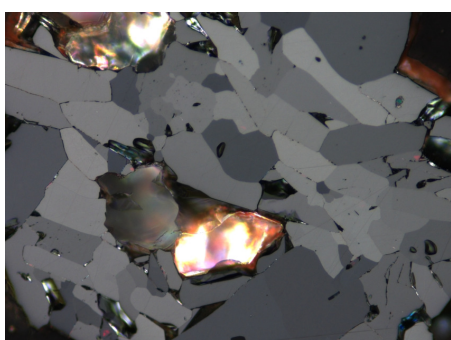


Figure 2. Crystallographic image 1: image obtained on RLM with the polarizer rotated about 30° from the crossed nicols arrangement.

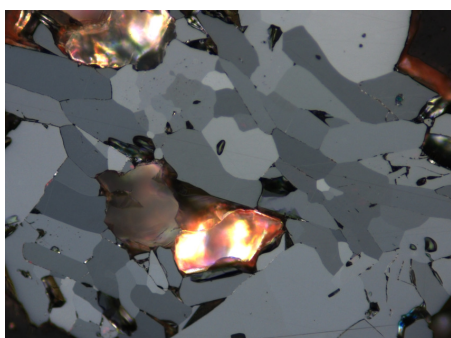


Figure 3. Crystallographic image 2: image obtained on RLM with the polarizer rotated about -30° from the crossed nicols arrangement.

The polarizer/analyzer configurations of 30° and -30° from the crossed nicols arrangement were used to make the proposed methodology reproducible. In practice, the methodology can also work with images acquired rotating the polarizer by a different step from an extinction point.

B. Image analysis

The image analysis procedure followed a routine that is comprised basically by the following sequence:

- Segmentation of hematite.
- Coarse segmentation of hematite grains.

- Fragmenting of hematite grains.
- Generation of seeds of hematite grains.
- Region growing of the seeds in order to form the segmented hematite grains.

The segmentation of hematite is carried out through thresholding of the mineralogical image acquired on the RLM without the analyzer. The hematite binary image thereby obtained constitutes a mask that is used in the following image processing steps to remove any pixel outside the hematite phase. Actually, in the present methodology the mineralogical image is used just for segmenting hematite from the rest of the image.

To make the coarse segmentation of hematite grains, the classical Canny edge detection method [10] is applied to the two crystallographic images in order to determine the grain boundaries. Therefore, two binary images of boundaries are obtained. These images are merged and the resultant image is subsequently subtracted from the hematite binary one. The result is a binary image that roughly contains hematite grains.

Nevertheless, the latter procedure is not capable of identifying all hematite grains. It only furnishes a coarse segmentation. In fact, some of detected regions are two or more adjacent grains that have similar crystal orientations and consequently present similar color in crystallographic images.

On the other hand, this first binary image of hematite grains is useful as a first approximation. Then, it is partitioned through the watersheds technique [11] in order to separate joined grains. To guarantee that all grains are separated, the watersheds must be over applied. This procedure actually leads to a binary image in which the grains are separated, but they are extremely fragmented too (Figure 4).

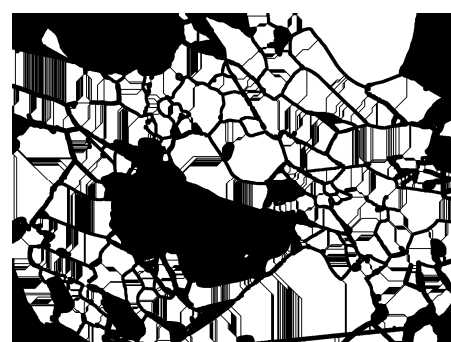


Figure 4. Binary image of fragmented hematite grains.

Then, the morphological operation of ultimate erosion [12] is applied to this image. Therefore, the fragments are reduced to a set of seeds composed by one pixel each. Finally, the hematite grains are correctly discriminated through a region growing segmentation method [13], using the seeds.

The region growing algorithm employed in this paper is quite different from the classical one. It is fed by both crystallographic images as well as by the seeds image. Before region growing segmentation, a median filter is applied to the crystallographic images in order to reduce salt and pepper noise.

A pixel connected to a grain is considered as belonging to it if its maximum spectral distance in RGB space from the corresponding seed pixel in crystallographic images is smaller than a fixed threshold. Specifically, a pixel $p(x,y)$ connected to a grain g that is defined by the seed pixel $p(x_g,y_g)$ pertains to the grain g only if the following rule is obeyed:

$$d^g(x,y) < t \quad (1)$$

where $t = 0.03$; and $d^g(x,y)$ is the maximum spectral distance in RGB space between the corresponding pixels of $p(x,y)$ and $p(x_g,y_g)$ in both crystallographic images, computed as

$$d^g(x,y) = \text{Max}(d_1^g(x,y), d_2^g(x,y)) \quad (2)$$

$$d_i^g(x,y) = \begin{bmatrix} R_i(x,y) \\ G_i(x,y) \\ B_i(x,y) \end{bmatrix} - \begin{bmatrix} R_i(x_g,y_g) \\ G_i(x_g,y_g) \\ B_i(x_g,y_g) \end{bmatrix} \quad (3)$$

where i is 1 or 2, indicating the crystallographic image 1 or 2, respectively; $d_i^g(x,y)$ is the spectral distance in RGB space between the corresponding pixels of $p(x,y)$ and $p(x_g,y_g)$ in the crystallographic image i ; and $R_i(x,y)$, $G_i(x,y)$, $B_i(x,y)$ are the RGB values of the corresponding pixel $p(x,y)$ in the crystallographic image i .

The region growing algorithm evolves finding grains automatically. If two or more grains are overlapped, they are united. Figure 5 presents the resulting image of segmented hematite grains for the field shown in previous figures. In this image, each grain is labeled with a different color. Figure 6 shows the edges of the detected grains superimposed on crystallographic image 1.

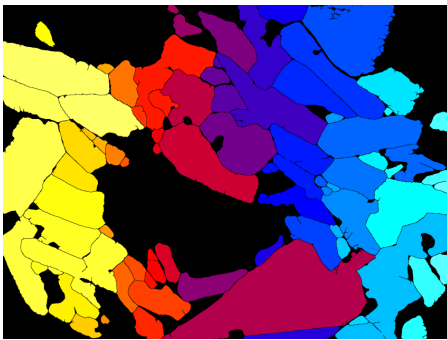


Figure 5. Labeled hematite grains.

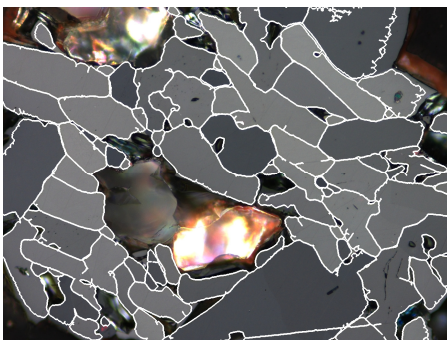


Figure 6. Grain boundaries (white) superimposed on crystallographic image 1.

III. DISCUSSION

The results are promising. The vast majority of grains were correctly identified. Even adjacent crystals with similar colors were discriminated.

The method is essentially automatic once the images have been captured. The only adjustable parameter is t , which controls the sensitivity of pixel spectral distance in RGB space.

However, some limitations must be pointed out. Given its discrimination capability, the method is also sensitive to problems in sample surface due to specimen preparation, such as scratches or relief. Figure 6 shows these two types of defects: a fake boundary in the lower part due to a scratch and a displaced boundary on the top right crystal, due to relief. Actually, this field of view was chosen to show these problems. Nevertheless, a suitable sample preparation can mitigate them.

It is also important to mention that the image acquisition step may be labor intensive, as it requires three images for each field (sample location), and tens of fields are normally required to provide a representative sampling of the material. Although field scanning is motorized and computer controlled in the microscope used, polarizer rotation is manual. As future work, the authors intend to motorize the polarizer rotation procedure.

IV. CONCLUSIONS

A novel method for automatic discrimination of crystals employing polarized RLM was developed.

The method employs traditional image processing operations and proposes an optimized spectral distance classifier to control region growing from automatically obtained seeds.

It is worth mentioning that the proposed region growing procedure is very robust and is able to deal with the excessive number of seeds derived from the watershed segmentation. This allows the use of a simple sequence of traditional image processing steps, readily available in many softwares.

Its application to hematite crystals in iron ore is a relevant step in ore quality control and opens the possibility of more sophisticated crystal morphology identification, which is currently under development. The method can also be applied to other anisotropic materials.

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