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# Automatic recognition of hematite grains under polarized reflected light microscopy through image analysis

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### ABSTRACT

The recognition of hematite grains is an intermediate task that aids the texture characterization of iron ores. Hematite is a strongly anisotropic mineral. Thus, the combined use of a polarizer and an analyzer in reflected light microscopy (RLM) can be used to obtain images that present sufficient contrast to differentiate grains. The present work proposes a methodology for recognizing hematite grains in images obtained with RLM. Three images per field are acquired in different conditions: without polarization in common bright field arrangement; and with polarization under two symmetrical polarizer/analyzer angles. These images are automatically registered. Then, the hematite grains are recognized through a modified region growing segmentation method based on reflectance and textural information. An optimal value for the polarization angle was determined. The results are promising. The vast majority of grains was correctly recognized. The automatically segmented images were compared to edited versions in which all crystals were correctly discriminated. A statistical comparison of crystal size and shape showed no statistical differences, to within 99% confidence, between automatic and edited segmentation results.

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# 1. Introduction

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, and texture analysis can contribute to the determination of the iron ores downstream beneficiation operations and subsequent steelmaking process, allowing improvements on both new and existing processes ([Vieira et al., 2003; Santos and Brandão, 2005\)](#page--1-0).

It is worth mentioning that the term texture may have different meanings. In Materials Science, texture refers to the distribution of crystallographic orientations of crystallites within polycrystalline materials. On the other hand, in Mineral Technology, texture is sometimes employed as a synonym of fabric to refer to the spatial distribution of different minerals in ore particles or in a rock. In this paper, texture is used in a broad sense. It refers to the spatial distribution of grains within a mineral and to the spatial distribution of different minerals within particles.

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 [\(Criddle and Stanley, 1993](#page--1-0)).

Automatic image analysis systems are capable of identifying hematite, magnetite and goethite by their colors on suitable RLM images. In recent years some methodologies ([Pirard and Lebichot,](#page--1-0) [2004; Donskoi et al., 2007; Gomes and Paciornik, 2008a,b\)](#page--1-0) were developed to perform mineralogical characterization of iron ores through image analysis systems.

Practically the majority of Brazilian iron ores are of the hematite prevailing type. These ores have a simple mineralogy, generally involving hematite, magnetite, goethite and some gangue minerals, mainly quartz. 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 ([Criddle and Stanley, 1993\)](#page--1-0), i.e. its reflectance and consequently its brightness in images changes with different crystal lattice orientations under plane polarized light. This brightness variation is subtle, but it is perceptible to a trained human eye in the RLM.

On the other hand, the combined use of a polarizer and an analyzer in the RLM promotes brightness and color variations due to anisotropy ([Gribble and Hall, 1992](#page--1-0)). This approach can be used to obtain images that present sufficient contrast to



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differentiate grains. [Pirard et al. \(2007\)](#page--1-0) developed an image processing methodology to detect 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 new approach to perform automatic recognition of hematite grains in images obtained with the RLM. Both polarized and traditional bright field images are combined in an image acquisition, processing and analysis routine that allows discriminating hematite from other phases and detecting the boundaries between hematite crystals. Several polarizer/analyzer setups were tested and optimal discrimination conditions were identified. The count, size and shape of the detected crystals was then automatically obtained and compared to results from manual discrimination for accuracy check.

## 2. Methodology

## 2.1. Image acquisition

A motorized and computer controlled RLM with a digital camera (RGB, 24 bits, 1300  $\times$  1030 pixels) was employed to acquire images from polished cross-sections of iron ore samples. Five different fields were selected for their content of hematite regions.

Three images per field were acquired:

- A bright field (BF) RGB mineralogical image obtained without polarized light (Fig. 1a).
- Two polarized light RGB images for which the exit analyzer was kept fixed and the entry polarizer was rotated to two symmetrical positions close to the extinction condition (crossed Nicols). These images will be referred to as POL +  $\theta$  and POL  $- \theta$ , where  $\theta$ is the rotation angle from extinction. Fig. 1b and c.

As crystal discrimination depends on the contrast between adjacent crystals, it also depends on the angle  $\theta$ . Thus, five values of  $\theta$  ( $\pm$ 5°,  $\pm$ 10°,  $\pm$ 15°,  $\pm$ 20°,  $\pm$ 30°) were tested, and the results compared to search for an optimal value. Non symmetrical angular image pairs were also tested.

## 2.2. Image processing and analysis

### 2.2.1. Pre-processing

During image acquisition a displacement between BF and POL +  $\theta$ /POL  $\theta$  images was detected. It probably occurs because polarizer/analyzer are mounted slightly oblique to the optical axis to avoid spurious reflections in the microscope. Although small, in the order of one pixel in the  $x$  and  $y$  directions, this misalignment created fake crystal boundaries. Thus, before any further processing, each triad of images was registered by an automatic routine through the traditional cross-correlation approach [\(Zitova and](#page--1-0) [Flusser, 2003](#page--1-0)). The displacement increased with the angle  $\theta$ , but was always automatically corrected by the routine.

#### 2.2.2. Segmentation

The aim of segmentation is to distinguish the relevant components of the image. In the present case, these components are the individual hematite crystals. However, to reach this goal a novel approach was developed, comprising several steps.

- 1. Segmentation of hematite regions: The segmentation of hematite was carried out through intensity thresholding of the BF image. As hematite is much brighter than the other present phases, it is easy to select an intensity threshold from the image intensity histogram. The result is shown in [Fig. 2a](#page--1-0). The hematite binary image thereby obtained constitutes a mask that was used in the following image processing steps to remove any pixel outside the hematite phase.
- 2. Coarse segmentation of hematite grains: In this step a first detection of grain boundaries was attempted, to be refined later. The classical [Canny \(1986\)](#page--1-0) edge detection method was applied individually to the lightness component of each POL image, and the obtained binary images were combined through the logical operation "or". The resulting edge image was then subtracted from the hematite image from step 1. The main limitation, at this point, was that the detected edges were many times incomplete and did not form closed boundaries around crystals. Moreover, edges between adjacent crystals with similar color were not always detected.
- 3. Super-segmentation of hematite grains: To complete missing or broken edges, a binary watershed technique was applied to the coarse segmented image from step 2. The inverted Euclidean Distance Transform was employed to process this image, and then the watershed segmentation ([Beucher and Lantuéjoul,](#page--1-0) [1979](#page--1-0)) was applied. This procedure actually lead to a binary image in which the grains were separated, but many of them were strongly fragmented. The use of Euclidean Distance Transform in a binary watershed procedure can promote over-segmentation ([Chen et al., 2004\)](#page--1-0), which is desirable in the present case. See [Fig. 2b](#page--1-0).
- 4. Generation of grain seeds: Each grain fragment from the previous step went through an ultimate erosion [\(Serra, 1982](#page--1-0)) and was thus reduced to a single pixel seed. See [Fig. 2c](#page--1-0). These seeds were then used in a sequence of grain growing and merging, described in the following.
- 5. Grain growing and merging: A modified region growing method [\(Gomes et al., 2010\)](#page--1-0) was applied to the seed image so that each seed grew back to a crystal. Because the seeds came from a super-segmented image, there must be a way to merge growing



Fig. 1. (a) Bright field image; (b) polarization image 1 – polarizer angle = +10°; (c) polarization image 2 – polarizer angle =  $-10^{\circ}$ .

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