

## Automatic Classification of Hematite in Iron Ore

*K.S. Augusto<sup>1</sup>, J.C.A. Iglesias<sup>1</sup>, L.D. Durand<sup>1</sup>, O.Gomes<sup>2</sup>, D. Pirotte<sup>1</sup>, A.L.A. Domingues<sup>3</sup>, M.B. Vieira<sup>3</sup> and Paciornik, S.<sup>1</sup>*

*<sup>1</sup>DEQM PUC-Rio, <sup>2</sup>CETEM/MCTI, <sup>3</sup>CTF/Vale, Brazil*

*karenaugusto@yahoo.com.br*

### Keywords

Iron Ore, Optical Microscopy, Circular Polarization, Phase Analysis, Pattern Recognition.

### Introduction

One of the main steps in the quality control of iron ore involves the analysis of images obtained under the optical microscope (OM). Traditionally, the experienced technician visually distinguishes the main phases, estimating their surface fractions and, in certain cases, crystal or particle sizes and shapes.

The main phases present in Brazilian iron ores are hematite, magnetite, goethite and silicates. Hematite is predominant and represents a big analysis challenge because it appears in different textures, both in polycrystalline particles and single crystals. Thus, hematite is classified in 3 main textural classes - the non-compact (nCP) hematite phases - martite (Ma) and microcrystalline (Mc) - and compact polycrystalline (CP) particles. These compact particles are formed by crystals with different sizes and shapes that must also be measured. Thus, each crystal must be discriminated and classified as granular (Gr - equiaxial grains), lamellar (La - elongated grains) and lobular (Lo - non-convex shapes).

A procedure for automatic classification of hematite in iron ore is proposed in this paper. OM images obtained in different contrast modes are processed and combined. Texture parameters are used in a first pattern classification step to discriminate between Ma, Mc and CP. CP particles are then submitted to a specialized Region Growing (RG) segmentation [1] and undergo a second classification step to discriminate between Gr, La and Lo crystal types.

### Materials and Methods

Samples of Brazilian hematitic iron ores were prepared for observation under reflected light in the optical microscope. Figure 1 summarizes the whole image processing and analysis procedure.

Images were acquired in Bright Field (BF - Fig. 1a) and Circular Polarization (CPOL - Fig. 1b) [2]. Figures 1c, d, e and f, show magnified views of typical CP and nCP hematite. In BF the crystals forming the CP particles are barely visible (Fig. 1c) while in CPOL they appear in different colors due to their crystalline orientation (Fig. 1e).

In the BF images hematite is always the brightest phase. If image acquisition conditions are kept stable, it is possible to segment the hematite regions with a fixed threshold (Fig. 1g). This segmented image was used as a mask for the CPOL image, eliminating all other phases, as shown in Fig. 1h.

This masked CPOL image undergoes a first pattern recognition procedure to discriminate between CP (Fig. 1i), Ma (Fig. 1j) and Mc (Fig. 1k) particles. Employing a supervised classification procedure, representative samples of each class were selected



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by an experienced user, and Haralick parameters were measured. Several classifiers were tested in the Octave software environments.

CP particles are fragmented into individual crystals (Fig. 1l) with a RG segmentation method based on the RGB difference between seed pixels and their neighbors. The seed pixels are automatically obtained as described in [1]. The individual crystals then undergo a supervised classification procedure based on shape parameters, and are classified as Gr, La or Lo (Fig. 1m).

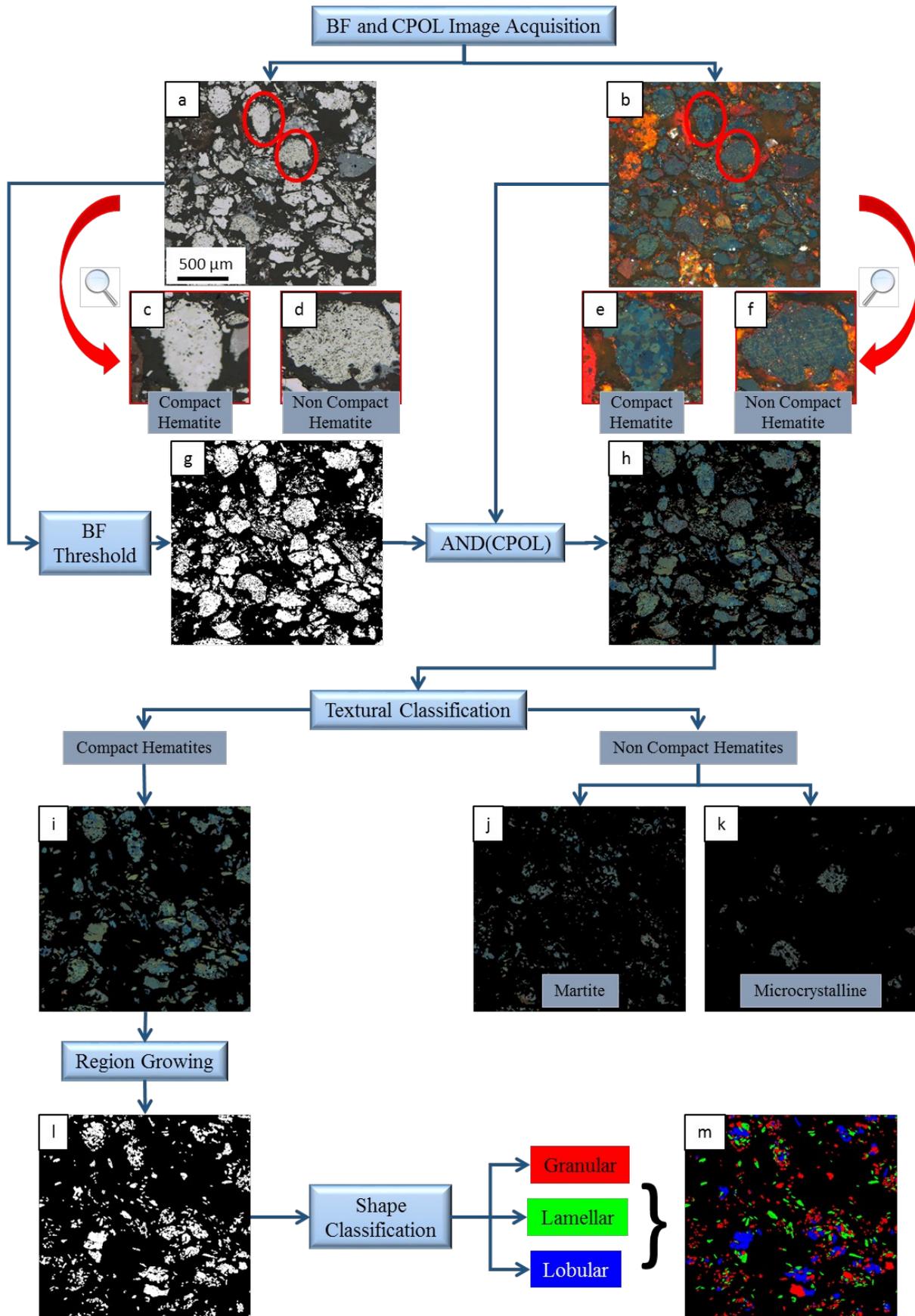


Figure 1. Flowchart for image Acquisition, Processing and Analysis

## Results and Discussion

The training database for textural classification comprised 189 images for CP, 84 for Ma and 40 for Mc. This is a relatively small database, especially considering the intrinsic variability in microstructures. However, selecting and identifying representative particles is very time consuming and it was interesting to test the performance in these realistic conditions. Moreover, the texture is measured in a window (a textel) of 50x50 pixels that moves across the image, leading to a much larger number of 10444 samples.

The 11 first Haralick parameters [3] were measured for 0, 45, 90 and 135 degrees, but the average and the range of the 4 directions were used, adding to 22 parameters, further increased to 44 features by including and not including zero valued pixels in the calculations. Dimensionality reduction was achieved with Linear Discriminant Analysis, reducing the parameter space to 2 dimensions (= number of classes -1).

The Octave Quadratic classifier showed the best results. Cross validation employed the division of the training database into halves, training the classifier with one half and testing on the other half. Thousands of random divisions were tested and the average successful classification rate (CR) for all divisions was used. The average cross validation CR was 71.01%, 81.58% and 88.31% for Ma, Mc and CP, respectively. The lower success rate for Ma is related to the microstructural variations of this phase.

The training database for shape classification is much larger, as it comprises individual crystals obtained with the RG method. Thus, 2518 samples were used for Gr, 2298 for La and 188 for Lo.

Six shape parameters, as described in [2], were used as features. The Octave Quadratic classifier again showed the best results. Cross validation was performed as described above, with nearly 9000 divisions. The average cross validation CR were 99.23%, 98.95% and 99.48% for Gr, La and Lo, respectively. These very high success rates highlight the fact that shape classification is relatively straightforward, as compared to the complexity of textural classification. The main issue is the quality of the RG method, which might distort the detected crystals. A recent change in the acquisition method for CPOL images, with a strong increase in color saturation and contrast, should improve this detection.

## Conclusion

Classification of hematite textural types and crystal shapes was achieved with an image processing and analysis procedure.

The combined acquisition of BF and CPOL images allowed the automatic selection of hematite particles.

Textural classification of particles in the CPOL image allowed their classification into Ma, Mc and CP classes, with success rates above 80% for Mc and CP. Further separation of Ma regions into 2 subclasses to take into account microstructural variations is under development and should improve the classification results. The classification of crystal shape was very successful, with CR close to 100%.

Further increase in the training database is under way and is expected to improve the overall quality of the procedure.

## References

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