GRAIN SEGMENTATION OF HEMATITE-RICH ORE BY MULTIVARIATE ANALYSIS OF POLARIZED LIGHT IMAGE STACKS[1]

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Abstract
The aim of the present work is to classify co-registered pixels of stacks of polarized light images of iron ore into their respective crystalline grains or pores, thus producing grain segmented images that can be analyzed by their size, shape and orientation distributions, as well as their porosity and the size and morphology of the pores. Polished sections of samples of hematite-rich ore are digitally imaged in a rotating polarizer microscope at varying plane-polarization angles. An image stack is produced for every field of view, where each image corresponds to a polarizer position. Any point in the sample is registered to the same pixel coordinates at all images in the stack. The resulting set of intensities for each pixel is directly related to the orientation of the crystal sampled at the corresponding position. Multivariate analysis of the sets of intensities leads to the classification of the pixels into their respective crystalline grains. Individual hematite grains of iron ore, as well as their pores, are segmented and quantified. Imaged fields of view are analyzed in terms of the area fractions of grain classes and the results are compared to those obtained by visual point counting methods.
Key words: Microscopy; Image segmentation; Grain; Iron ore.

SEGMENTAÇÃO DE GRÃOS EM MINÉRIOS RICOS EM HEMATITA POR ANÁLISE MULTIVARIADA DE PILHAS DE IMAGENS DE LUZ POLARIZED

Resumo
O objetivo do presente trabalho é classificar, nos seus respectivos grãos cristalinos ou poros, pixels co-registrados de pilhas de imagens de minério de ferro adquiridas com luz polarizada, produzindo desse modo imagens segmentadas em grãos que podem ser analizados quanto às suas distribuições de tamanho, forma e orientação, do mesmo modo que sua porosidade e o tamanho e a morfologia dos poros. Seções polidas de amostras de minério rico em hematita são fotografadas digitalmente em um microscópio com polarizador giratório em ângulos variáveis de polarização plana. Uma pilha de imagens é produzida para cada campo observado, onde cada imagem corresponde a uma posição do polarizador. Qualquer ponto na amostra é registrado em um pixel de mesmas coordenadas em todas as imagens da pilha. O conjunto resultante de intensidades de cada pixel está diretamente relacionado à orientação do cristal amostrado na posição correspondente. A análise multivariada dos conjuntos de intensidades leva à classificação dos pixels nos seus respectivos grãos cristalinos. Grãos individuais hematita no minério de ferro, bem como os seus poros, são segmentados e quantificados. Os campos de observação fotografados são analisados em termos das frações de área das classes de grãos e os resultados são comparados àqueles obtidos por métodos de contagem de pontos.
Palavras-chave: Microscopia; Segmentação de imagens; Grãos; Minério de ferro

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INTRODUCTION

Adequate prediction of the behavior of particulate ore material in industrial processes requires the characterization of the particle populations in terms of their chemical composition, texture, morphology and liberation. In recent years many authors have suggested that textural features are of critical importance.[1] The meaning of texture in ore particle characterization is twofold: it is broadly understood as the spatial distribution of both different minerals and different grains or crystals of the same mineral in a particle. Many authors prefer the word fabric for the first kind of distribution and explicitly refer to texture when the orientation in crystalline assemblages is described.[2] Regarding to the first meaning, King and Schneider[3] have demonstrated that the mineralogical ore texture has a decisive influence on the liberation distribution. The size, shape and spatial distribution of crystals and pores, on the other hand, influence the reducibility of sinters.[4]

The development of useful image analysis software for routine quantitative textural analysis of ore particles demands an automatic (or at least semi-automatic) identification, on a pixel by pixel basis, of the mineral species as well as pores and grains. In other words the objects of interest (grains and pores) must be segmented, i.e., all the pixels in the image must be classified into their respective crystalline grains or pores. The assignment of each pixel to only one grain or pore defines the set of pixels forming every object of interest in the image and allows morphological measurements to be made. However, in spite of the many available imaging instruments and image analysis methods, this task has long remained as the most difficult to be automated. Orientation imaging by automatic indexing of electron backcscatter diffraction patterns after phase identification by EDX is the most promising strategy when the properly equipped SEM is available. However, these are expensive and time consuming techniques, particularly when a large number of samples is to be analyzed.

Pirard[5] have recently introduced multispectral imaging of ore minerals in optical microscope and performed supervised image analysis by multivariate pixel classification techniques that have long been used in remote sensing. It is clearly shown that multispectral images obtained with a set of narrow bandwidth (10 nm) interference filters lead to larger separation of the mineral phases in the color space. This result can in principle be extended to other ores by the appropriate choice of the interference filters, i.e., by choosing filters that produce the largest contrast between all pairs of minerals. Pirard also comments on extending the principles involved in multispectral image analysis to multiradial images for handling optical anisotropy. The potential of using the composite data from a set of images of the same sample acquired with changing polarization direction of the polarizing filters to enhance the ease and accuracy with which grains can be identified has been previously pointed out by Fueten,[6] who developed a computer-controlled rotating polarizer stage for the petrographic microscope. In more recent work, Pirard and co-workers[7] have stacked multispectral and mutiradial images to identify iron oxides and perform particle texture analysis. The mapping of individual hematite crystals was obtained by adding a bireflectance intensity criterion to the segmentation process.

Regarding the image analysis methods, pixel classification has been usually performed with active assistance of the user, who sets parameters like thresholding grey levels, or selects representative regions of the objects of interest. These methods can be efficiently automated if the image acquisition conditions can be fixed and the imaged objects have the same features in all images, which is hardly the case in ore mineralogy where optical properties like bireflectance and pleochroism do not allow a one to one correspondence between color or brightnes and mineralogy or grain orientation. In order to automate the identification of objects having variable appearance, an adaptive method must be applied. Even though performed without assistance of the user, being thus called unsupervised, these methods must be selected considering the characteristics of the problem at hand and thus require some a priori knowledge about the imaged objects and the imaging conditions.

Among the unsupervised pixel classification methods, those employing the mean shift algorithm[8-12] seem to have strong potential for application in quantitative microscopy.[13] Mean shift is a tool for finding modes in a multivariate data set first described in Fukunaga e Hostetler,[8] and more recently discussed in Cheng et al.[9] It is application independent, can handle arbitrary feature spaces; doesn't assume any prior shape on modes or data clusters; doesn't require the previous knowledge of the number of clusters, is robust under sampling errors and thus suitable for real data analysis. .It is also simple and straightforward to implement, being based on the iterative shifting of a fixed size hypersphere to the average of the encompassed data points in the feature space. Of course it also has some shortcomings. One parameter (the radius of the searching hypersphere) must be set by the user, and this is not trivial. Inappropriate choice of this parameter can cause modes to be merged, or generate additional false modes. When applied to grain segmentation the first case implies that different grains are connected and in the later, that one grain is partitioned, or oversegmented. Use of adaptive hypersphere radius has been proposed as a general solution, but an experienced user can set this parameter once for a given image batch.

Even in optimal conditions the resulting pixel classification will always display some assignment errors due to sample preparation imperfections, optical aberrations and image acquisition artifacts. Misclassification is efficiently resolved by introducing a post-processing step where spatial information is added by morphological operations.

The aim of the present work is to take advantage of the complementary information from a set of images of the same sample acquired with changing polarization direction of the polarizing filters in order to automate the segmentation of hematite grains and pores of an hematite-rich iron ore by applying a mean shift based pixel classification algorithm. The segmented objects are the elements of the ore particle structure or texture. From the grain segmented images it is straightforward to evaluate the lamellar or granular character of the hematite grains, the porosity of the mineral assemblage, the size and shape distributions of grains and pores.

METHODS

The hematite rich iron ore concentrate from Quadrilátero Ferrífero (MG, Brazil) studied in the present work represents an ore with high deformation and metamorphic grade. The particle size is within the range from 0.50 to 1.00 mm.

For optical image analysis the sample is mounted in an epoxy resin block, which is polished in one side and digitally imaged under a Leica DM150 reflected light optical microscope with a rotating polarizer by a Sony Exwave HAD™ color video camera using the Leica IM50 program. Visual inspection reveals that the sample is a hematite-rich iron ore composed basically of hematite mineral and pores. This hematite is a secondary mineral generated by high metamorphism and deformation, which yield coarse well-crystallized hematite crystals with regular contacts and triple junction boundaries. The crystals are mainly granular with subordinated lamellar grains giving an incipient foliation to the ore. This simple texture is well suited for testing image analysis procedures.

From representative regions of the sample, a series of images are acquired from the same scene when rotating the incident light polar, using polarization steps of 2.5° All images are acquired under a 10x objective lens and digital sampling of 1300x1030 pixels, with a resulting resolution of 1478 pixels/mm, as determined by imaging a stage micrometer. In order to build reflectance maps of narrower spectral band, only one color component of the color image is considered. Since the video camera uses a Bayer filter, the green channel is chosen due to its higher resolution. Background correction is performed in all images to compensate for non-uniform illumination across the image. For this purpose, a white reference image is acquired of a highly uniform surface without any inclusions or scratches using the same objective lens and illumination as the image to be corrected. The images of the same scene are stacked together with multiradial information, as described next.

The polarized light intensities I^{θ}, reflected from any point in the sample, as imaged in the green channel of the video camera, at all polarizer positions θ, are co-registered to the same pixel coordinates (x, y) in all images of the stack. The resulting set of intensities $\left\{I^{\theta}(x, y)\right\}$ for each pixel $P(x, y)$,

$$P(x, y) = \left\{I^{\theta}(x, y)\right\}, \quad \theta = 0, 2.5^{o}, ..., 15^{o},$$

is directly related to the orientation of the crystal at the corresponding positions. These intensities are the features of the corresponding pixels.

Let us now represent each pixel by a feature vector $\mathbf{x}_i = [I^0, I^{2.5}, ..., I^{15}]$ in a feature space which dimensions are the intensities I^{θ}. Since the grains and segmented pores are homogeneous objects, their pixels have similar intensities at every polarizer orientation and therefore their feature vectors tend to cluster in the feature space, forming high density regions, or modes. Each grain or pore is then represented by a cluster in the feature space. Feature space analysis (clustering) is the procedure of finding these clusters.

Comaniciu and Meer[10] have developed a color image segmentation technique based on the mean shift property. It can be directly applied to multispectral and multiradial image analysis by extending the number of dimensions of the “color” space.

The content of a continuous feature space can be modeled as a sample from a multivariate, multimodal probability distribution $f(\mathbf{x})$ of finding a feature vector between $\mathbf{x}$ and $\mathbf{x} + d\mathbf{x}$. In the image segmentation problem, it is the probability distribution of finding a pixel with a given set of intensities. Define the hypersphere $S_h(\mathbf{x})$ of radius h centered on $\mathbf{x}$ and containing n_x data points in the feature space. It can be shown [11] that the sample mean shift is

$$M_h(\mathbf{x}) = \frac{1}{n_{\mathbf{x}}} \sum_{\mathbf{x}_i \in S_h(\mathbf{x})} \mathbf{x}_i - \mathbf{x} \sim \frac{\nabla f(\mathbf{x})}{f(\mathbf{x})}$$

This means that the mean shift vector points towards the direction of a local estimate of the normalized gradient. Therefore, the direction of the maximum increase in the density can be obtained by computing the sample mean shift. From the above equation, a procedure can be implemented by recursively moving the center of the hypersphere by the mean shift vector and then recalculating the mean shift. The track of the consecutive mean shift vectors is a path leading to a local density maximum, i.e., to a mode of the density.[11] Every starting point of this mode seeking procedure is associated with the respective final mode. In addition, by associating the points with the modes, the structure of the data (number of clusters and their shapes) is revealed. In the image segmentation problem, every pixel is assigned to a grain or pore which are then identified and measured.

RESULTS

Four images from a typical multiradial image stack are shown in Figure 1.

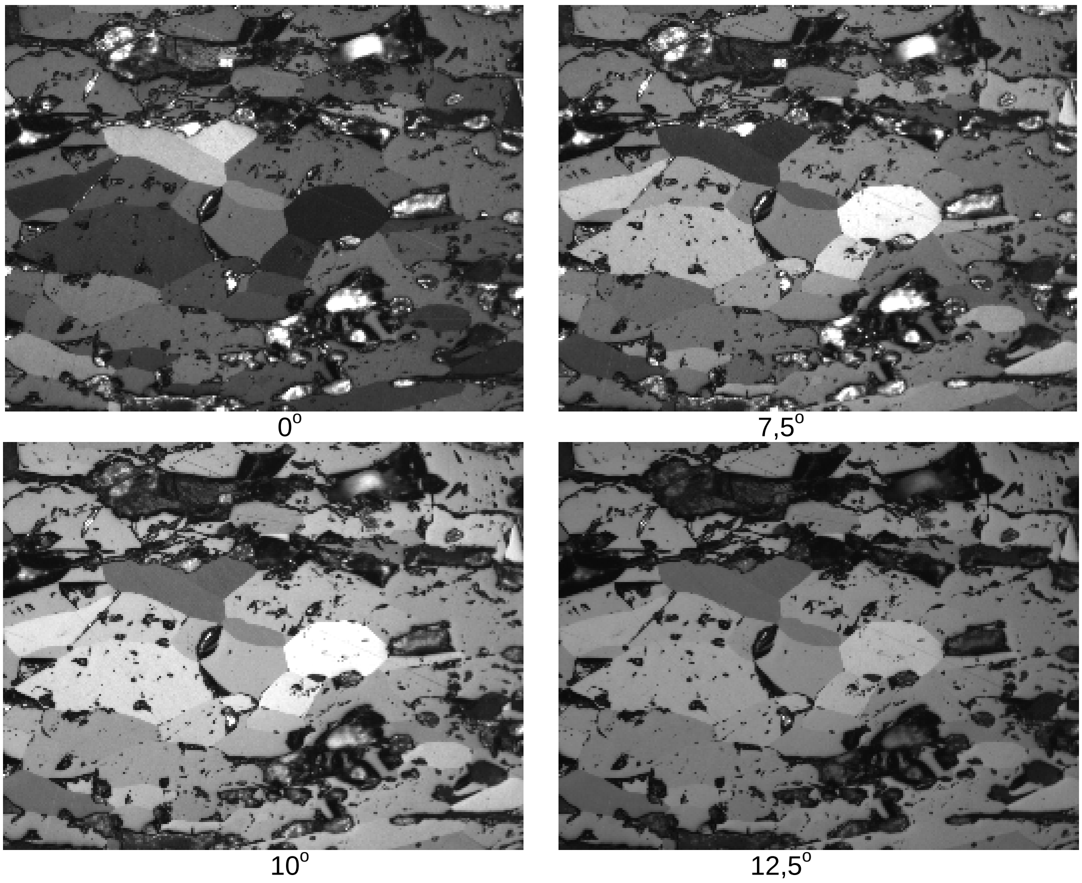

Figure 1 – Polarized light images acquired from the same region of the hematite-rich iron ore samples at four different rotating polar angles. (10x objective lens = 0,88mm imaged field width)

The pores exhibit many artifacts for almost all polarization angles. These are identified as modes by the mean shift procedure. This problem is circumvented by first segmenting the pores and then using the resulting binary image as a mask to eliminate the artifacts in the other images. Segmentation of the pores can be accurately performed by applying the simple Otsu criterion to the image acquired with the polarizer at $\theta=15^o$. Figure 2(a) shows the pores mask image.

Multiradial information is best viewed using false color. Thus, Figure 2(b) presents a false color composition (RGB) of images from the set of Figure 1 (7.5^o, 0^o, $12{,}5^o$), after pores segmentation.

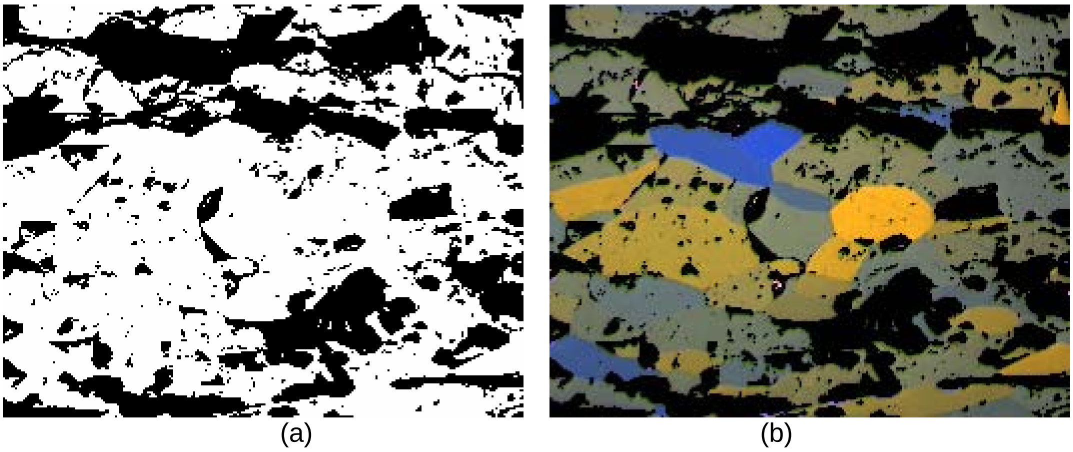

Figure 2 – (a) Pores mask image as obtained by simple threshold of the image acquired with the polarizer at $\theta = 15^o$. (b) False color composition (RGB) of images from the set of Figure 1 (7.5^o, 0^o, $12,5^o$) after filtering

The feature space spanned by the polarized light intensities reflected by the sample can be partly represented in the three dimensional RGB color space. Figure 3 shows the clusters in the false color space associated to the grains of the region in the insert. The figure was generated by the software COLOR SPACE 1.1 (P. Colantoni, 2005, http://www.couleur.org).

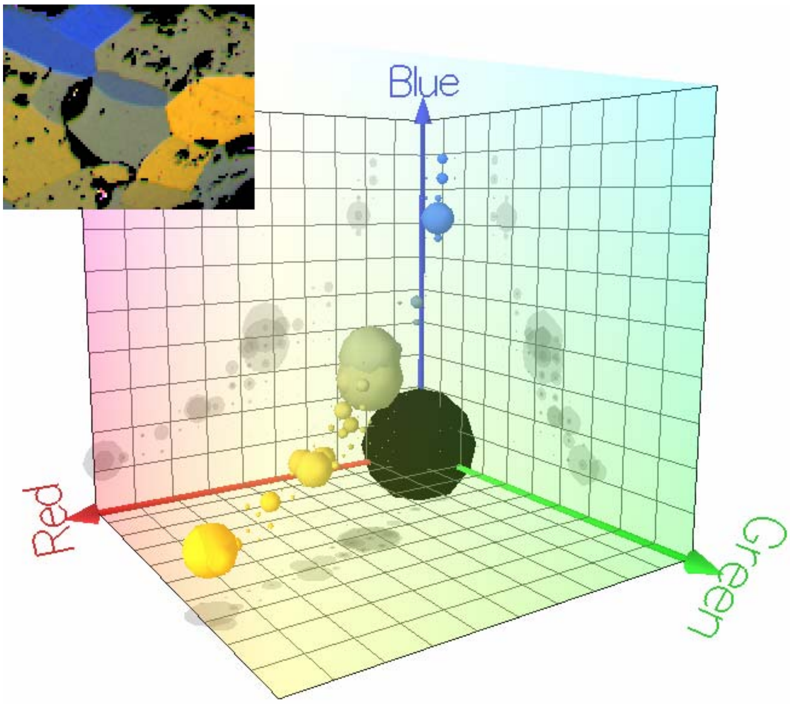

Figure 3 – Clusters in the feature space corresponding do the grains and pores of a region (insert) of the image in Figure 2(b). (Image generated by the software COLOR SPACE 1.1 – P. Colantoni (2005) – http://www.couleur.org)

After applying the mean shift procedure to the image of Figure 2(b), and assigning every pixel to a cluster in the false color space, the image results segmented into its grains and pores. The segmented crystals are then classified according to their aspect ratio into granular and lamellar. The area fractions of grains and pores obtained from the mean shift segmented image are compared to the results of image quantification using the traditional modal counting in Table 1.

Table 1- Comparison of the area fractions of grains and pores obtained from the mean shift segmented image and by image quantification using the traditional modal counting.

Minerals	Counting	Mean shift
Granular Hematite	30,00	29,47
Lamelar Hematite	37,22	35,39
Pores	32,64	35,14
Total	99,86	100,00

CONCLUSIONS

In the present work we analyze the multivariate data obtained by multiradial imaging of an hematite-rich iron ore using a mean shift based pixel algorithm in order to classify the pixels into their respective hematite grains ore pores. From the grain segmented images we evaluate the porosity of the mineral assemblage and the lamellar or granular character of the hematite grains. Our results show good agreement with those obtained by image quantification using the traditional modal counting. The mean shift algorithm seems to be a good alternative to automate the identification of homogeneous objects having variable appearance.

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