DETERMINATION OF APPARENT APATITE GRADE BY DIGITAL IMAGE ANALYSIS

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ABSTRACT

According to the Brazilian Department of Mineral Production the phosphate rock world production in 2010 was something about 176 millions of tons and the national production were 6.192 millions of tons. The Brazilian phosphate rock production is concentrate in alkaline-carbonate complexes localized in Tapira, Araxá, Catalão and Cajati counties. It is well known that the greater comprehension of the mineral intrinsic characteristics lead to a good understand in processing of this mineral. This paper presents a mineralogical characterization and apatite grade estimation using digital image analysis. Different samples of phosphate rock from the primary grinding homogenization stock pile were used. The samples were donated by Vale Fertilizantes Company (which was responsible for 72% of the Brazilian production of phosphate rock in 2010), situated in Catalão-GO. The samples was dried, granulometric classified using a Tyler screen series and photographed using a digital camera coupled in a stereoscopic microscope (with increase of 10X/20). A software using Borland Delphi 7 was developed to perform the analysis of the digital images acquired using a colorimetric differentiation. The mineralogical grades of apatite determined through the software were compared to the grade determined through chemical analysis of twin samples to the characterized. The found results indicated that the digital image analysis can be used as a complementary technique to the actually mineral characterization methods, such as the chemical methods, once this analysis is faster and cheaper than the others methods and it is a non-destructible method.

1. INTRODUCTION

According Fonseca (2011) the phosphate rock world production in 2010 was something about 176 millions of tons. In sixth place the Brazilian produced were 6.192 millions of tons, corresponding to 3.5 per cent of world production. The Brazilian phosphate rock reserves are placed in Mina Gerais (66%), Goiás (13%) and São Paulo (6%), being the production concentrate in alkaline-carbonate complexes localized in Tapira, Araxá, Catalão and Cajati counties.

Optical microscopy, often referred to as the “light microscope”, has being used as the most utilized microscopy technique from over three hundred years. Among its advantages includes the low cost, easiness to use and transmission/reflection contrast. Digital images increasing utilization has create new researches areas in computation. The development of digital images processing new techniques have being used in many areas, such as engineering, health, physics etc. This integration between areas results in works which try to solve, using computational methods with acceptable computational time and cost, complex problems difficult (or time demanding) to solve without the computation support.

Digital images are replacing the conventional pictures which were analyzed using manual techniques. Digital images do not lose his attributes (such as color and bright) over the years and can be enhanced with specific algorithms. The industrials utilization of digital image analysis has being used in exchange of conventional techniques due its speed, lower cost and the possibility of perform on line analysis.

The possibility of study mineral features using digital analysis has motived many works. Peres et al. (2011) proposed a method to rock classification based in its color, extracting rock texture features using a border detection algorithm. For the color analysis the authors had used the RGB (red, green and blue) pallet which consists in a hexadecimal number who retain the color information of each pixel of the digital image. Color frequency histograms were generated and its decoding allowed the authors to characterize the mineral samples. According to the authors the proposed system can be easy adapted and installed in conveyor belts or analysis mills products.

A colorimetric sensor (composed by a video camera connected to a video capture board, a personal computer and a software) for mineralogical composition estimation was developed by Oestreich et al. (1994) assuming that color vectors (a common color format used for TV set calibration) produces better results than RGB pallet once the measurement the angles of color vectors is less vulnerable to lightning variations or presence of shadows in the sample. The authors used the sensor in froth flotation samples, slurry and dry mix of minerals containing chalcopyrite a molybdenite.

Another technique wide adopted for mineral grade estimation using digital image analysis consists in the creation of a neural network for the image segmentation (Moolman et al., 1995). Chatterjee et al. (2010) working with limestone from an Indian mine and found estimated results compatible to the one found by chemical analysis. To do so the authors created a multi-layer perceptron neural network (MLP) model and due the implementation of three neural layers was possible to obtain the grade of five chemical compounds: CaO, Al_2O_3, SiO_2 e Fe_2O_3.

2. MATERIAL AND METHOD

Sample preparation

The phosphate rock samples used in this paper was donated by Vale Fertilizantes, situated in Calão County. The samples were acquired from stock piles generated after the primary crushing and were destined to feed the mineral processing plant. Five samples with 750 grams, each one from a different stock pile, were tested. Table 1 shows the samples chemical composition.

Table 1. Samples chemical composition.

P_2O_5	Fe_2O_3	AL_2O_3	MgO	SiO_2	CaO	BaO	SrO
20.89	21.46	3.00	6.44	18.39	14.32	3.53	0.41

Digital image analysis performs mineralogical grade estimation, not chemical. Considering this fact data in table 1 needed to be converted from chemical to mineralogical data allowing the comparison between the results from digital image analysis and chemical analysis. Therefore was adopted the following mineralogical composition for the samples: apatite [$Ca_5(PO_4)_3(OH,F,Cl)$], hematite [Fe_2O_3], vermiculite [$(MgFe,Al)_3(Al,Si)_4O_{10}(OH)_2.4H_2O$], barite [$BaSO_4$] and strontianite [$SrCO_3$]. Table 2 shows the mineralogical grade of the samples, estimated from table 1.

Table 2. Tested samples mineralogical composition.

Apatite	Hematite	Vermiculite	Barite	Strontianite
36.34	21.46	36.93	4.74	0.53

The samples were dried in a drying oven regulated at 180 ± 10^{o} C for an hour. After that the samples were separated into smaller samples (250 g) and size classified by dry screening. The dry screening used 17 stainless steel Tyler screens with 8” diameter and 15 minutes of screening. Figure 1 shows sample particle size analysis. The particles retained at each screen were stored as a new subsample and labeled with a letter.

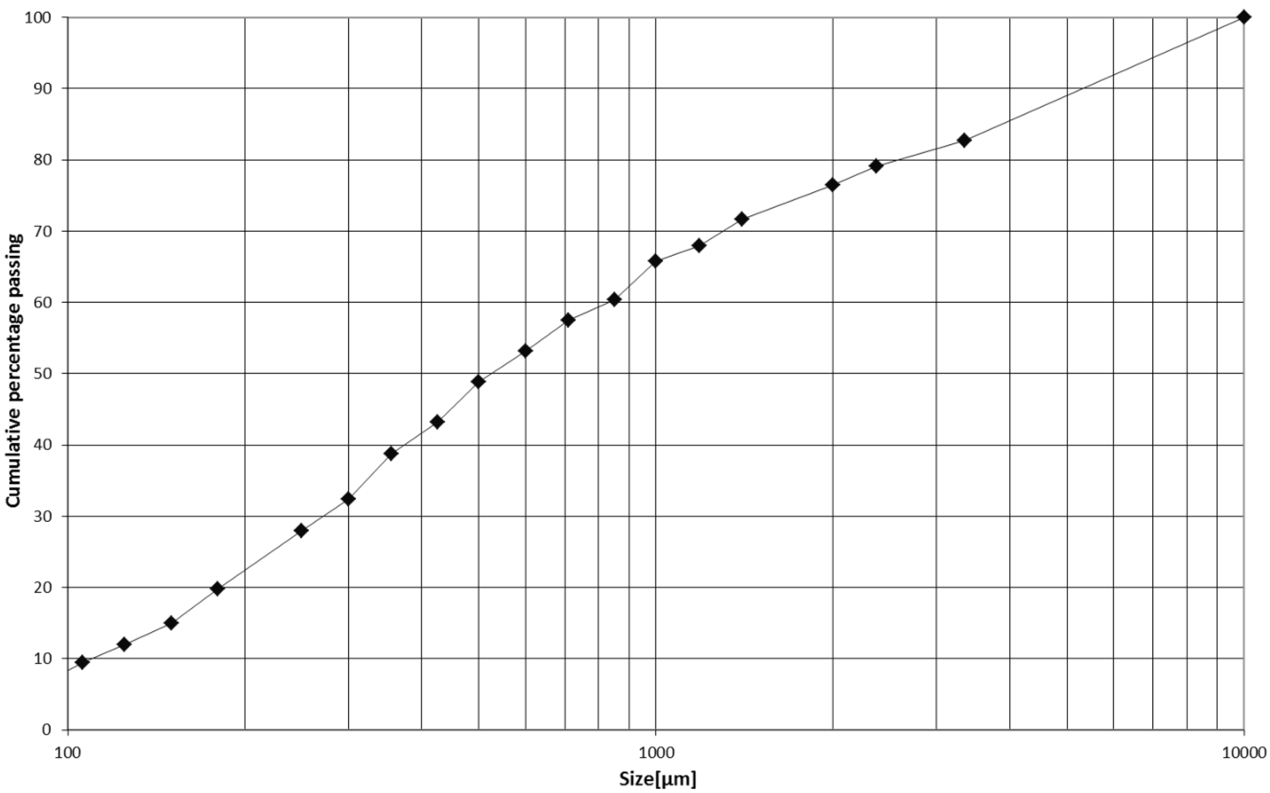


Figure 1. Sample particle size analysis.

Digital image acquisition

The digital images were acquired using a Sony DSC-S730 (7.2 MP) camera coupled into a Diagtech stereo microscope ZOOM 645. Figure 2 show the assembly used to acquire the digital images.

Figure 2. Assembly used to acquire the digital images: Sony DSC-S730 (7.2 MP) camera coupled into a Diagtech stereo microscope ZOOM 645.

Random samplings were performed in each subsample to acquire an even smaller subsample (around 5 g) and from each smaller subsample were taken 4 digital images, in a total of 68 digital images.

Digital image analysis

Using Borland Delphi 7 integrated development environment a software was developed to perform digital image analysis. The mineral phases in the image are analyzed through colorimetric differentiation of the phases. The color used at each analysis was select by the software user during the analysis. The algorithm used to complete analysis an image was:

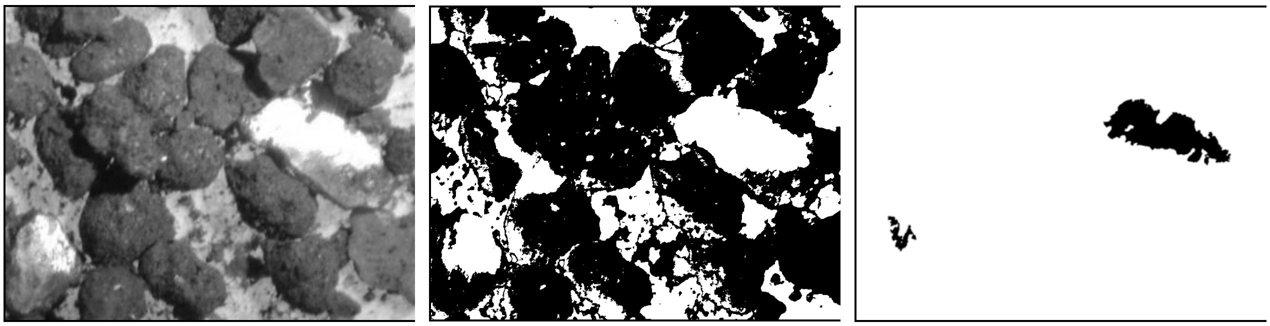
1. *Colorimetric scan*: in this step a complete scan is performed in the image selecting which pixels of it agree with the select color by the user. It´s also possible to choose a tolerance range for the selected color. At the end of the scan a new image is generated containing only two colors: black and white, where black pixels represent the pixels in the original image which agrees with the select color range and the white pixels are the ones which does not agree with the select color range;

2. Noise removal: after the colorimetric scan small clusters of pixels are generated (the size of each one being less than one per cent of the total image area). These clusters, called noise, are generated form imperfections in the image acquire assembly or even in the colorimetric scan. An algorithm to remove these clusters was developed. The user simply select the size of the clusters to be removed and a new noiseless image is generated;

3. *Mineral particles counting and labeling*: with the image properly treated after the two previously steps the minerals particles can be labeled and counted. To do so the Hoshen and Kopelman (1976) algorithm was used.

3. RESULTS

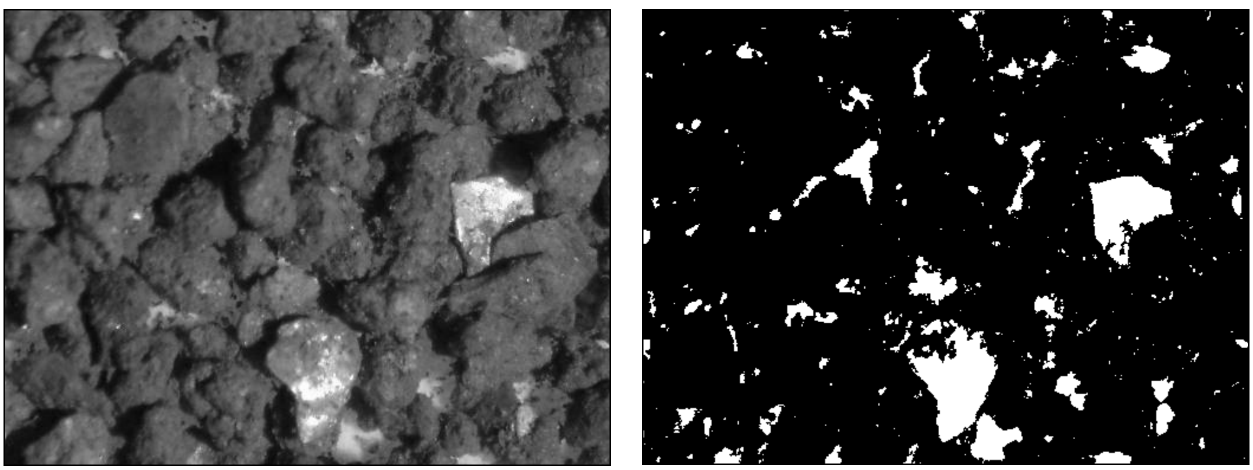
The minerals in the samples were divided into three different groups regarding to its distinguishing facility. Group A, composed by apatite, barite and strontianite; Group B, composed by iron oxides (hematite and magnetite) and Group C, composed by micas (usually vermiculite). Figure 3 shows the result of an analysis: figure 3b is the analysis result for Group A and figure 3c for Group C. The lighting influence in the results can be seen when figures 3a and 3c are compared, once two mineral particles from Group C were only partially identified due mica high reflectivity.



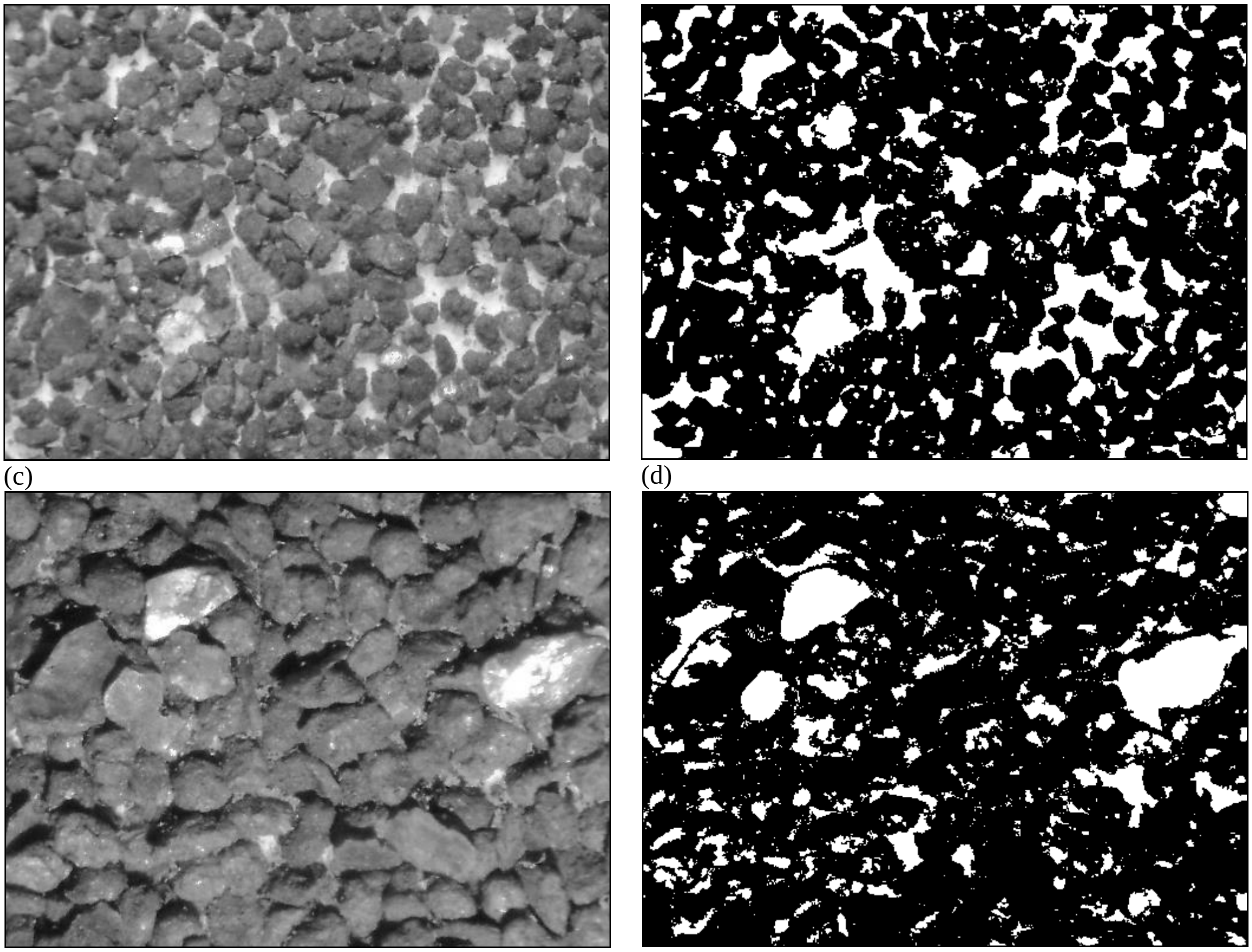
(a) (b) (c)

Figure 3. Digital image analysis results: (a) sample digital image to be analyzed, (b) results for minerals in Group A and (c) results for minerals in Group C.

Figure 4 shows three different subsamples images, each one was analyzed and the results are presented in table 3. The digital image analyzes were performed in a personal computer with Intel Pentium T4500 processor and 3GB RAM. For any image the processing time was less than 2 seconds.



(a) (b)



(c) (d) (e) (f)

Figure 4. Tree different images analyzed with different particle sizes: (a) -48+60#, (c) -20+24# and (e) -24+32# sample.

Table 3. Results from figure 4 analyses.

Image	Particle size	Image area [pixels]	Processing time [s]	Group A grade
4a	-48+60#	197505	1.920	91.26
4c	-20+24#	197505	1.948	81.68
4e	-24+32#	197505	1.981	86.89

Figure 5 shows grade values obtained from digital image analyses (represented by gray bars) and the chemical grade (represented by dark line). The chemical line was draw as a sum of minerals from Group A (apatite, barite and strontianite) and Group C (micas, usually vermiculite). Even the software being able to analyze mineral from each group same mineral particles were misanalysed.

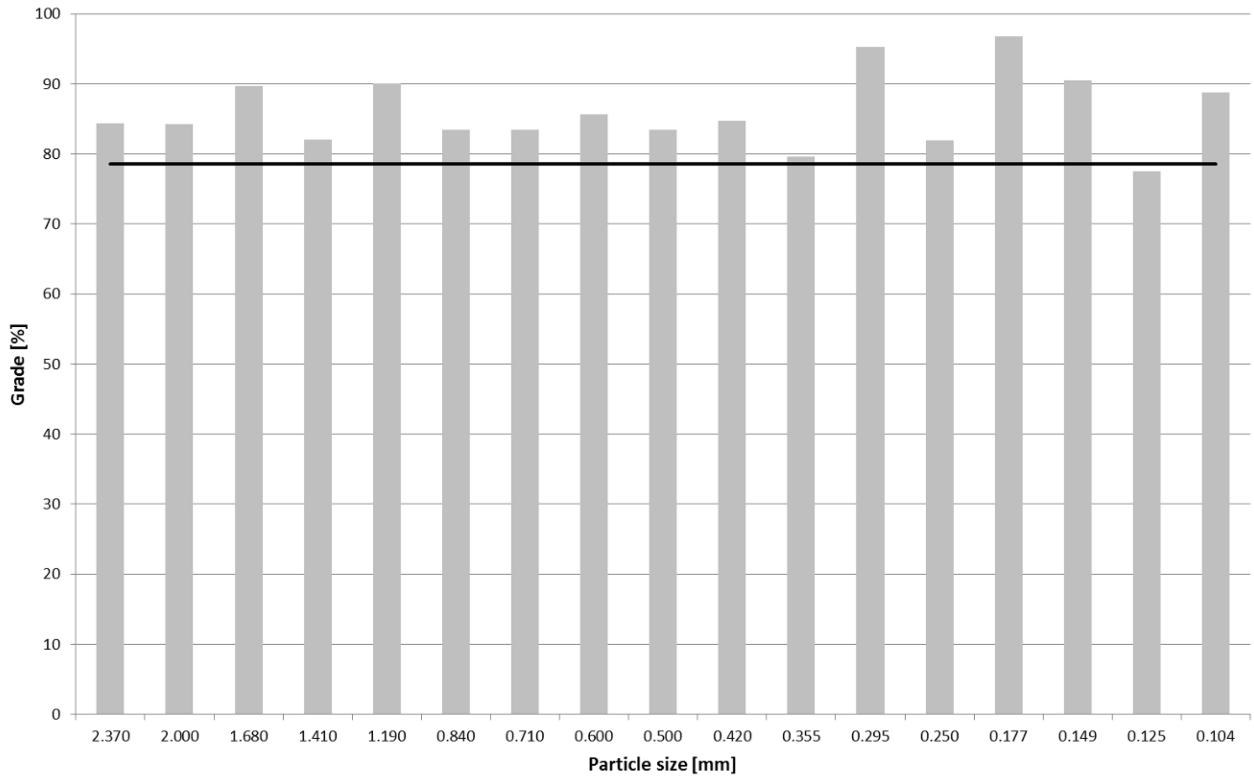


Figure 5. Estimated grade for each particle size (represented by gray bars) versus chemical grade (represented by a dark line).

4. CONCLUSIONS

A major problem noted was the used light in images acquisition was not adequate. The ideal illumination cannot cast shadows in the sample or even generate shadows due its own topography, which can be solved by using sliced samples put together with resin. To solve the illumination problem a device with four identical lamps will be developed and installed around the microscope. We noted that mineral from Group A attached superficially to minerals from Group C, leading the software only partially identification of the mineral. This problem has no relation with particle liberation and a scrubber step could probably solve the problem though this step reduced the phosphate rock size.

Besides the noted problems the results founded indicated a great potential digital image analysis in mineral industry as a complementary technique for mineral characterization techniques used in this days, since this analysis is faster and low cost. Future work is required to enhance the software quality as well as improve the image acquire system.

5. ACKNOWLEDGES

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6. REFERENCES

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