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Weak Rocks Disintegration Patterns Recognition through Image Analysis

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Abstract

This paper presents results about image analysis application for identification and classification of disintegration patterns upon weak rocks, clay-bearing rocks and Intermediate Geomaterials IGMs. The research was conducted in order to obtain a reliable method for field and laboratory because upon these materials, it is quite difficult to acquire unaltered samples due to the quick disintegration after the materials are exposed to environmental conditions. Thus, the application of image analysis and color changes produced by disintegration advance has shown reliable results to be used as an alternative method to replace the traditional human eye based classification charts. Several images were taken upon different disintegration states and environmental conditions and were correlated with changes in color channels, using colorimetric indices and statistical image descriptors. As a result, a disintegration classification method based on Image entropy and color changes was stated, the findings were validated and compared with results from traditional methods using both natural and artificial samples with controlled disintegration levels, in addition, Hyperspectral images, were used as well.

1. Introduction

Nowadays, Geologists and Geotechnical engineers are facing a great challenge to interpret the data retrieved from slopes with advanced stages of disintegration (Figure 1). The disintegration of weak rocks, soft rocks, very weak rocks or intermediate geomaterials IGMs occurs quickly when they are exposed to climatic conditions. It makes characterization and quantification of these materials extremely difficult at different disintegration states, even upon laboratory controlled conditions. Commonly, disintegration assessments have been performed by means of observational processes compared to predefined disintegration patterns associated with different disintegration states (Figure 2). These patterns are included in different classification schemes, which have been stated, founded on expert knowledge and empirical approaches according to experimental work made upon a specific type of rock or geomaterial. For instance, the slake durability rating SDR proposed by Erguler and Ulusay [1] is a classification chart developed to measure disintegration on clay-bearing rocks, it stated 6 disintegration states and their correspondent visual patterns based on the fracture frequency (λ) such as the presented on the (Figure 2). Fracture frequency (λ) is the inverse of fracture spacing and $SDR = 100–100 * \lambda$. The chart was developed on laboratory and field-based observations of disintegration characteristics of different clay bearing rocks. It includes six rating classes, designated as I through VI, with their corresponding disintegration patterns, fracture frequency (λ) values, SDR values, and related information about other physical properties (Rincon, Shakoor et al.[2]). However, application of these disintegration classification systems is based on human observations and could be subjective by skills and abilities. Additionally, their applicability to laboratory samples is limited due to the material scale and high disintegration susceptibility because of its fast alteration. Hence, because of those uncertainties, the computer vision was used in this research looking for an improvement in the classification process, applying tools widely used in other science fields. Thus, in this paper, the most relevant experiences and findings about computer vision application upon disintegration assessment are summarized.

Figure 1. The Same mudstone in different disintegration states a) Low b) medium c) high.

The majority of reported image applications related to geomaterials disintegration have focused on crack detection.The experimental work has been performed generally using homegeneous clay samples in slurry state, leaving beside hetereogeneous materials as the exhibited in Figure 1. Likewise, the studies have applied traditional segmentation algorithms based on gray scale transformed image, in order to correlate the results with different properties (i.e. plasticity, specific surface and water content). Nevertheless, in spite of the diversity of studies, textural features as voids and fine fragments related to disintegration process have not yet been adequately considered in image analysys. It is due to the interest in principal fracturing systems detection, by means of preprocessing techniques for removing the clods or the islands. Referring to disintegration quantification, these textural features play an important role; consequently, the abovementioned technics using a grayscale-transformed image are not enough to get a reliable quantification. Therefore, an image analysis process that comprises color structure changes and alterations on the images was required in order to develop a new methodology improving segmentation outcomes and a better disintegration assessment.

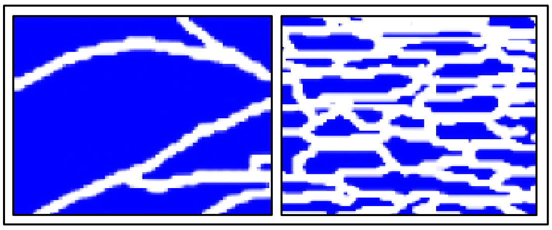


Figure 2. Example of disintegration patterns from SDR chart a) low b) high.

2. Color alterations on visible images related to disintegration of weak rocks

Color has been defined in different ways along the history. Despite color has been widely studied in several science fields, nowadays its definition is not satisfactory at all (Viet, [3]). Color's definition has been widely linked with human perception through its senses. Thus, it set the color notion as the result of light interaction with a certain body, and how a human being perceives that interaction. So, considering the relationship between the geomaterial disintegration advance and color changes, it would be possible to discern that the resultant color on a disintegrated material is affected by textural features increase, the color alterations on geomaterial surface can come in two ways: changes on voids or changes on spots. The problem is that these alterations are not easy to quantify using traditional human eye classification approaches such as Munsell charts (Munsell Color Firm, [4]). Thus, in order to appreciate how color alterations are, different experimental artificial vision setups were developed upon laboratory samples under controlled conditions, other to samples exposed to natural climate conditions and other on cut slopes in the field. The analysis was made at global or local image level, assessing the changes on different color descriptors, and looking for disintegration feature related anomalies on them. On the other hand, different artificial samples were created using Modelling oil-based clays because they are not affected by moisture changes caused by evaporation, are malleable, and have color stability; these models were used to simulate different disintegration patterns and conditions and color changes produced by disintegration alterations (Figure 3).

Hence, based on all experimental results, a clear change on the surface dominant color structure was identified between different disintegration stages on these types of materials and this alteration is well mapped by blue channel histogram changes. For instance, Figure 3 shows how surface affectation increases change the resultant blue tones distribution on the accumulated pixel count histograms for two different clay models; this figure displays the accumulated blue histograms for both samples at two different surface affectation levels. The models were made in two different colors (skin and black), looking to verify the response for materials with colors located on the low-key tone region (dark tones) and the high key tone region (bright tones).The results confirmed that the color variations (especially in the blue channel) had mapped fairly well the disintegration changes on the surface of the sample; despite which tonal range the material dominant color is, Therefore, it suggests that color image properties would be better disintegration evolution indicators than grayscale, converted images, which are traditionally used.

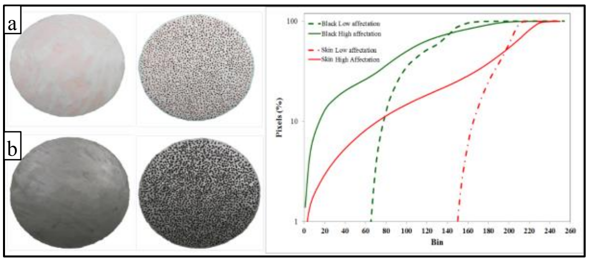


Figure 3 Accumulated histograms variations on clay models a) Skin on the top b) black on the bottom.

The change in the blue channel has not deeply considered hitherto because the majority of the studies had used greyscale transformed images, this transformation causes losses of relevant color information related with disintegration. For instance, Figure 4 shows how a conventional grayscale conversion (using the same weight for each color channel histogram), would generate an image in which the histogram tends to be located in the mid-tone region, producing information loss on the dark tones region; it is in this region where information related to disintegration is concentrated. So, the significance of blue channel changes related to disintegration was verified through reflectance measurements using a Hyperspectral Scanner in the visible and near infrared range (VIS-NIR). Figure 5 shows the change in reflectance in three different surface affectations upon a clay model; the blue line corresponds to the unaltered zone which has the higher reflectance (designated by the letter "a" on the image); the red line corresponds to a shallow affectation zone (designated by the letter "b" on the image), whereas green line corresponds to a profound void (designated by the letter "c" on the image). These measurements reveal how for the most affected zone corresponding to the deeper void the light absorbance is major in the blue color wavelengths region.

3. Color indexes

Some studies had been made relating color indexes and different geomaterial properties, applied mostly to soils (Levin, Ben- Dor et al.[5]; Madeira, Bedidi et al. [6]; Mathieu, Pouget et al.[7].; Torrent & Barron, [8]). These have been focused predominantly in seeking correlation with some mineralogical properties. The alterations in color have been parameterized through different color indexes using spectrophotometric and visible camera imaging systems. The colorimetric indexes have been used both in remote sensing and laboratory image analysis; these indexes had been recognized to be good predictors of soil for both types of analysis (Levin et al., [5]; Mathieu, Pouget et al [7]). In this research Coloration index (CI) (Eq. 1), Redness index (RI) (Eq. 2), Brightness Index (BI) (Eq. 3), Saturation index (SI) (Eq. 4), and Hue index (HI) (Eq. 5), proposed by Mathieu, Pouget et al. [7] and Madeira, Bedidi et al. [6] were studied in order to assess their reliability like disintegration descriptors. These indexes were incorporated into an in-house developed algorithm; in which complementary subroutines were coded in order to perform surface pattern analysis.

The algorithm was applied to images from samples with different disintegration states. A calibration process was made through a sensitivity analysis at single pixel level on both selected natural scene image locations and idealized artificial images, in order to understand the behavior of each index and correlate them with color parameters defining the range of values to use for disintegration associations.

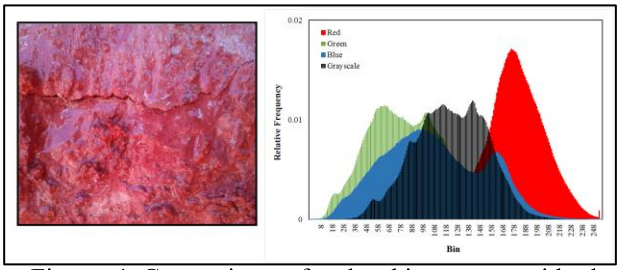


Figure 4 Comparison of color histograms with the grayscale histogram for a field mudstone image.

Coloration index

$$CI = (R - G)/(R + G) \quad \text{Eq. 1}$$

Redness Index

$$RI = R^2/(B * G^3) \quad \text{Eq. 2}$$

Brightness Index

$$BI = \sqrt{(B^2 + G^2 + R)^2/3)} \quad \text{Eq. 3}$$

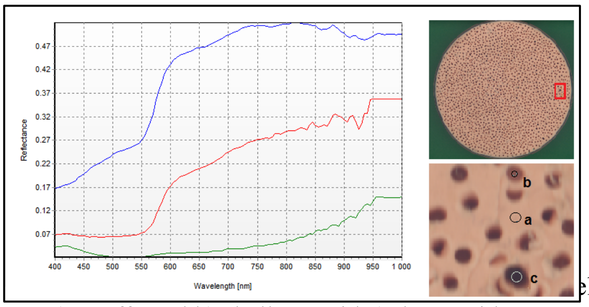
Saturation Index

$$SI = (R - B)/(R + B) \quad \text{Eq. 4}$$

Hue Index

$$HI = (2 * R - G - B)/(G - B) \quad \text{Eq. 5}$$

The results showed that the RI has a good performance differentiating principal cracks and deep voids; because its equation incorporates the blue tones, and blue color changes alter the IR drastically, IR variations could be used to make reliable differentiation between unaffected and affected zones. However, because the green color is also integrated on the IR equation, it causes IR to reduce its performance for materials in which their dominant color is between 520-580 nm. Subsequently, IR just could be used with good performance for materials in which the dominant color has dominant frequencies higher than 580 nm tending to Red color Hues zone. CI, showed a good performance on monochromatic clay models images (Figure 6), however, some classification mismatches were observed on natural mottled materials (Figure 7). It could be due to the blue color omission. So, it makes CI weak to be used as a disintegration classifier. SI and BI presented deficiencies in the classification process on natural mottled materials as well, so, the use of these two indexes could not be favorable as a disintegration classifier. Finally, the Hue Index (HI) has shown an excellent performance both classifying disintegration features on one-color clay models and mottled materials; the index shows good performance differentiating alterations according to their depth. Therefore, through the HI would be possible to classify features such as principal void structures, cracks, surface irregularities, fragments and fine cracks. Thus, relative changes in Hue index appear to be a good parameter in order to assess disintegration features and to estimate changes in the elements relative positions.



zones a) unaffected b) shallow void c) deep void

4. Image Entropy

Image entropy, is a statistical second order parameter reflecting the homogeneity of the image, it is a commonly used parameter for image analysis. The parameter, originally proposed by Shannon (1948) and denoted by the letter H, is defined as:

$$H = \sum_{i=1}^{L} P_i \log_2 P_i \quad \text{Eq.6}$$

Where Pi is the probability of the occurrence of the pixel value i, calculated from the ratio between each histogram cell that contains the observed frequency of the corresponding image intensity value and the total number of pixels in the image. The value of entropy is given in bits. According to Burger and Burge [9], entropy is a statistical measure that quantifies the average amount of information contained in the "messages" generated by a stochastic data source. Thus, a number of pixels, N, can be interpreted as a message of N symbols. From the point of view of the disintegration of weak rocks, the message could be associated with the changes in the values of intensities of each color, i.e. red, green, or blue (RGB), of each pixel in the captured image. The changes in entropy reflect modifications in the surface texture due to cracks, fragmentation, and voids. First, artificial binary images were created, based on the disintegration patterns included in the SDR chart by Erguler and Ulusay (2009). These images were then used to investigate the relationship between entropy (H), mean SDR for each class and mean fracture frequency (λ) The results show that an increase in entropy indicates a decrease in SDR value, and an increase in (λ) and affected surface area. Second, oil-based clays models were made. The models allowed sensitivity analysis of image entropy changes under controled conditions of size, light, color, surface irregularities, and sequence of disintegration. Finally, entropy was calculated for different laboratory samples and slopes images exhibiting different levels of disintegration. Thus, a theoretical relationship between entropy values obtained from the binary images, created to simulate the fracture patterns corresponding to SDR classes, and the mean fracture frequency (λ) for each pattern was made. The analysis initially showed that the range of possible entropy values for SDR classes is 0-8. Two of the suggested patterns in the SDR clasification system, do not follow the same trend as the other seven SDR classes or patterns. A possible explanation for this could be that the SDR patterns are based on the presence of only visible cracks captured by a binary image and do not consider microcracks, voids, and other irregularities.

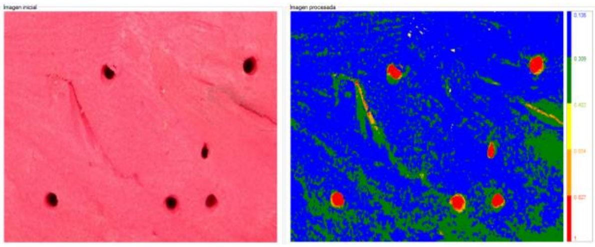


Figure 6 Coloration Index surface map unicolor clay model sample.

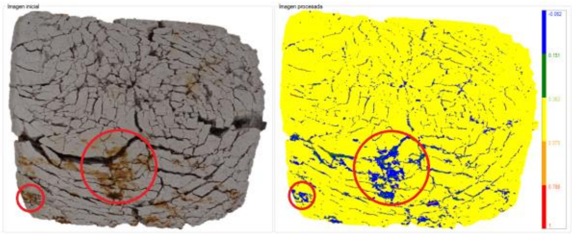


Figure 7 Detail of Coloration Index surface map mismatches on mottled zones.

The analysis revealed that the minimum entropy was 4.84 bits for clay models, whereas for rock samples, the minimum entropy value was around 5 bits, obtained from low disintegration rock fragments carefully selected during excavation process. Figure 8 shows entropy values for the same material in different disintegration states. On the top a carved sample entropy value of 5.89 bits, the entropy drops to 5.39 bits for the same image segmented without edges. The image of the same sample after five days of exposure to natural climatic conditions is presented on the left, thus the entropy increased to 6.46 bits. On the bottom the same material in the field is presented on the left two months after the excavation entropy was 7.1 bits. On the right after 32 months and the entropy increased to 7.7 bits. These results show that entropy increases with increasing degree of disintegration. This trend was verified using other materials with different lithological conditions and clay models with different colors and initial surface conditions. Finally, it was possible to find that the entropy varies linear with the affected surface and it reaches its maximum value 8 when surface is affected at about a 27%. Thus applying that relation, it was possible to define an effective correlation between image entropy and disintegration degrees.(low entropy values entropy less than 6 bits, medium degree of disintegration entropy values between 6 and 7 and high degree of disintegration entropies above 7 bits).

5. Conclusions

Through the provided experimental data summarized here, it was possible to establish that image analysis techniques can be used reliably in order to classify the disintegration state of weak rocks and Intermediate Geomaterials, it is possible by analyzing the surface color intensities variations, produced by the changes in light interaction due to disintegration features increase. If well; all color channels red, green and blue are affected, the blue channel histogram offers valuable information to identify disintegration features.

The image entropy can be used reliably as disintegration descriptor for characterizing and monitoring Weak rocks and Intermediate Geomaterials disintegration evolution both in laboratory samples and cut slopes in the field. It is useful to differentiate between materials of low, medium, and high degrees of disintegration.

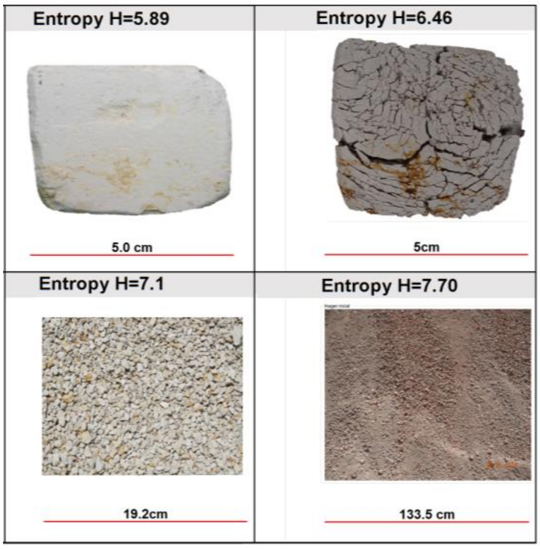


Figure 8 Example entropy value for samples and slopes exhibiting different levels of disintegration.

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