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ORE TYPOLOGIES CLASSIFICATION USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT: Many ores, particularly those of industrial minerals, present several typologies inside the geological deposit. The typological classification of a block can determine its value, processing route or if the block is worth being mined or not. In other words, it is vital information. This work presents a new mathematical technique for automatic classification of ore typologies using a self-organizing artificial neural network. This kind of network is fed with all the available information about the ore and, during the learning phase, the network finds itself the existent aggroupation patterns, generating its own classification. Once trained, the network represents a quick, versatile and reproducible classification technique. The results obtained with the spectro-colorimetric classification of Amazonie kaolins will be presented as an example of application of this technique.

1. INTRODUCTION

Finding the correct ore class! T^^ıior >s a CIL'C' mining problem especially f, ı iırlı.« nn niı c.'u.":. The rypologicul Classification ,',' d sji^ie or block is commonly used tu determine the future operations, processing routes and economic value of a mining unit. The principal classification method is the visual classification. The visual classification methods are based on the ore aspect as texture, color and granulometry. In these cases, an expert does the classification based on the visual observation of a sample. If the color is a good indicator for the classification, spectro-colorimetric data can be used for automating the classification. This approach can not only incorporate the spectro-colorimetric data, but also other factors like grade and granulometry in the classification of the typologies. This approach proved to be very effective to uncover a better typological classification. However, a large number of numerical data generated by the reflectance spectrum measures makes the analysis of the data and their correlation with the desired result difficult.

The solution found in this work was to design a self-organizing artificial neural network (Beale et al., 1991;Kröseetal., 1994). The use of this kind of neural network involves two steps. The first step is tlv: network design where the number of inputs is specified and the number of groups is defined. The next is the training step where a great number of spectral reflectance data is presented to the network until the change rate of the network weights becomes near zero and the same samples are classified as the same typology trail after trail. After training, the network is ready to classify the samples into the number of types that where specified İn the design of the network.

As a case study, the work on the classification of Amazonie kaolins based on its reflectance spectra will be presented.

2. THE VISUAL CLASSIFICATION PROBLEM

The relationship between the typology of the gross ore and its economic use is fundamental for the professional that acts directly in mining operations. The typologies are established generally in conformity with the deposit genesis, with the rock formations or with the mining method used. However, during the day-by-day operations the use of information about the typologies can become very difficult. There are also problems of ore continuity. These problems

confirm the importance of the constant monitoring of the material that is being exploited.
Usually the control of the types depends on the mining professionals' ability and experience. They are the key to the determination of which typology should be plowed. Not everybody can accomplish this work. Years of experience are necessary to develop the ability to visually classify the typologies using several factors as texture, color and granulometry. These limitations affect the control process, which is limited to a short period during the day or week and depends on the professional's physical conditions.

In order to solve the visual classification dilemma a tool was studied based on scientific and technical measures to take advantage of the interactive phenomena among light, color and material. This study aims to overcome the following problems (Lozano, 1978; Minolta, 1994):

a) Different spectra can generate the same color: ores contaminated by different elements or in different proportions can visually represent the same color, but in the processing phase, they can demonstrate completely different behaviors.
b) Different observers can present different impressions on the same sample: naturally creating a discrepancy in the classification.
c) Changes of illuminant can modify the observer's impressions: probably one of the most common problems, the in-door rooms are illuminated artificially, while out-door is illuminated by the daylight.
d) Differences in the sizes of the samples can hinder the observer's classification: another very common problem, the working samples can vary from grams to tons.
e) Background differences can induce to mistake: samples observed with a black background when compared with samples with a white background will confuse the observer.
f) Differences of humidity of the samples: the rains alter the natural humidity of the ore that this being plowed, creating classification problems.

3. NEURAL NETWORK DESIGN

The neural network used {Valim, 1998) has two layers of neurons (Figure I). One is the data input layer (input neurons) and the other is the classification output layer (output neurons). There are so many input neurons as the number of data available for one sample and so many output neurons as the number of desired typologies. All the neurons of the data input layer are connected with all the neurons of the classification output layer. Each connection has a weight (WJ_0) and the value of an output neuron is the sum of the squares of the differences between the input values and the associated weights:

$$y_o = \sum_i (w_{io} - x_i)^2 \quad (1)$$

Unlike some other kinds of neural networks, the neurons do not apply any kind of transfer function over the weighted sum of the inputs. The winning output neuron (k) is the one that presents the least value and determines in witch class (typology) the sample was classified:

$$k \mid y_k \leq y_o, \forall o$$

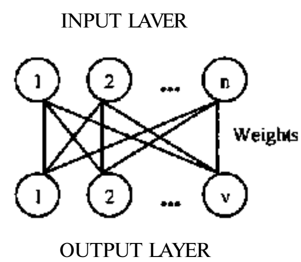

Figure 1: Generic layout of the two-layered self-organizing artificial neural network used.

4. NETWORK TRAINING

The network İs trained with a competitive learning method, where there are two training rates. The first is the rate for the winning neuron and the other is for all other neurons. The competitive rule is a variation of "the winner take all" (Kröse et a)., 1994). All the neurons learn the input data, but the winning neuron learns with a much greater rate. So, after one set of data is presented (time t) the new weights for the winning neuron are calculated by:

$$w_{ik}(t+1) = w_{ik}(t) + r_w[x_i(t) - w_{ik}(t)] \quad (2)$$

and the weights for the other neurons are calculated by:

$$w_{io}(t+1) = w_{io}(t) + r_l[x_i(t) - w_{io}(t)] \text{ , } o \neq k \quad (3)$$

where r_w is the learning rate for the winning neuron and IÏ İs the learning rate for the other neurons. Typical learning rates are like r_w=0.1 and ri=0.001, but each application will present different optimal values for these rates.

The data are presented and the network İs trained until the output of the winning neurons becomes near zero, the weights do not change more (or change very slowly) and the same samples are classified as the same typology trail {Valim, 1998).

5. KAOLIN TYPOLOGIES AND COLOR1METRIC CLASSIFICATION

In the kaolin deposit studied, nine lithologie types are identified in the field, based on the visual subjective classification of the color. The white color identifies kaolins of superior quality. The red color identifies non-economic kaolins, because they possess high contents of iron- and titanium-bearing contaminating minerals, undesirable in the ore. However, intermediary colors between white and red identify kaolins that can be or not to be considered economic, depending on the content of the contaminating minerals. In such case, the visual classification is not effective and it can commit the quality of the expected final product. To solve that problem, die use of colorimetric classification İs suggested with base in the form of the reflectance spectra of the lithologie types identified in the deposit. The spectrophotometric analysis of 44 run-of-mine (ROM) samples, embracing all the lithologie types, indicated six different shapes of spectral curves, constituting six different colorimetric groups, for which it was stipulated to denominate Groups A, B, C, D, E and F (Sabedot, 1997). The Figure 2 exhibits the shapes of the spectra of the groups.

The groups A and B characterize white-colored kaolins of superior quality. The groups C and D characterize kaolins of intermediary colors and quality. The groups E and F characterize non-economic kaolins, of intense red coloration (Sabedot et al., 1998).

Spectro-colorimetry is a tool that facilitates an objective classification, and whose results allow the application of neural networks. That method allows to define with more safety if the ore block can, or not, be submitted to a proper processing route, facilitating the obtaining of a final product with characteristics closer to the expected.

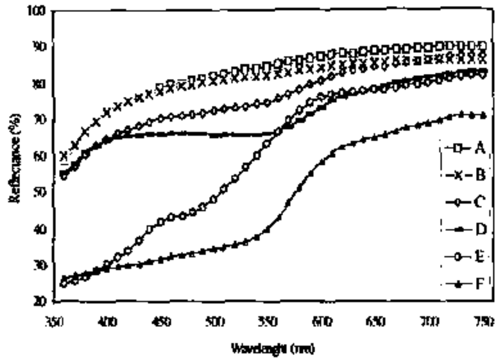

Figure 2: Generic reflectance spectra shapes of the 6 colorimetric groups proposed.

5. KAOLIN NEURAL NETWORK AUTOMATIC CLASSIFICATION

Therefore the results showed that the lithologie classification could be replaced with some advantages by a colorimetric-only classification. However, the main problem associated with the colorimetric classification is the large number of data generated by a reflectance spectra analysis. These data must be plotted and carefully analyzed for a good classification. At this point, there is no great difference between the lithologie and the colorimetric approach, since both need the subjective appreciation of an expert.

To solve this problem, it was found that the best approach is the use of a self-organizing neural network. This mathematical technique permits the automation of the classification phase, which can be integrated with the data acquisition with very simple algorithms.

For the training and testing of the technique it was used a database composed of 44 ROM samples. These samples were prepared and the reflectance spectra were measured from 360 to 750 nm with 10 nm spacing. A neural network with 6 output neurons was designed for generating a classification in 6 types. The same number of colorimetric types found in the previous work. As input data, the reflectance data were used with some generic transformations for improving the sensibility.

After the training phase, the classification of the 44 samples in 6 groups was tested and it was found that the neural network classification was mostly compatible with the previous proposed colorimetric classification. It must be noted that this kind of network works with unsupervisioned training. !n other words, it was not specified for the network witch was the desired classification, only that İt would be iri 6 groi'ps. The network found itself the best group or classifying the samples, based on the presented data.

6. CONCLUSIONS

The self-organizing artificial neural networks, associated with spectro-colorimetric analysis, are a quick and powerful technique for automatic and reproducible classification of industrial minerals based on their appearance. These neural networks produce a self-generated classification pattern that represents the best grouping of the samples based on the data presented. For the best results, a criterious data filtering is needed before the network feeding, for improving the network sensibility.

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