Neural Recognition of Minerals

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Abstract: The design of a neural network is presented for the recognition of six kinds of minerals (chalcopyrite, chalcosine, covelline, bornite, pyrite, and energite) and to determine the percentage of these minerals from a digitized image of a rock sample. The input to the neural network corresponds to the histogram of the region of interest selected by the user from the image that it is desired to recognize, which is processed by the neural network, identifying one of the six minerals learned. The network's training process took place with 160 regions of interest selected from digitized photographs of mineral samples. The recognition of the different types of minerals in the samples was tested with 240 photographs that were not used in the network's training. The results showed that 97% of the images used to train the network were recognized correctly in the percentage mode. Of the new images, the network was capable of recognizing correctly 91% of the samples.

1. Introduction

Chile is privileged in terms of rich mineral resources, particularly copper ores. One of the most important activities carried out by copper mining companies is prospecting for ores. Mining prospection requires a substantial amount of economic resources to determine the feasibility of going into a large investment to operate a mine. Prospecting consists in sampling rocks from different areas and determining the ore grade existing in those lands. To determine the grade of an ore the composition of the minerals present in the samples must be studied.

The procedure used to recognize minerals takes place by getting information on the different minerals that make up a rock. From these rocks obtained from the land that is being prospected, polished samples a quarter of an inch thick are prepared. Polishing of the samples provides smooth surfaces for analysis under a mi-

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croscope. The polished sample, which is called a **briquette,** is placed over a grid as a way to discretize the image under the microscope. In this way an expert quantifies the number of points covered or occupied by each *grain* of each mineral existing in the briquette to determine the percentage of that mineral in the sample. A grain is a section of the sample that contains a given mineral, and it is identified by the expert by referring to the visual characteristics of each mineral.

Both the process of recognition as well as the determination of the percentage is extremely slow and error-prone because of the excessive dependence on the attention of the expert in charge of the detection and counting of the points. An expert takes about 15 minutes to determine the total percentage of each mineral in a briquette.

In the literature there are applications for the automatic identification of minerals by different techniques. In [1] a digital image processing and texture analysis technique is shown for recognizing six kinds of rocks, with results showing 89% of correct recognition of 58 photographs. In [2] there is an automatic classification of the shape of graphite particles in cast iron. In [3] traditional multivariate statistical methods and extensions to address the problem of classifying minerals common in siliciclastic and carbonate rocks are applied. Other techniques like genetic programming have been developed in [4] to recognize mineral grains.

The classical algorithms are a viable alternative [5], however considering the associative processing implied in the use of neural engineering leads to fast and reliable automatic results. On the other hand, it contributes a practical application alternative to this important field of ore prospecting in Chile.

Section 2 details the problem and the design of the neural network (NN) to solve it; the process and the algorithms implemented are presented in section 3; section 4 shows the results obtained; and finally the conclusions are presented.

2. Analysis of the Problem and the Proposed Solution

In the first place it must be stated that the problem put forth is divided into two relevant areas: a) Recognition of the mineral; and b) counting points in the area associated with each grain, with the purpose of determining its percentage presence in the sample.

In order to design the NN's architecture to identify the patterns associated with each mineral, the learning process was started by training the NN with the previously digitized input patterns. The final product is a system that is capable of recognizing the mineral by inspection of the digitized image of a briquette. The input consists in the selection by the user of a region of interest (ROI) in the briquette, and the output is the identification of the mineral. Another alternative of the system is to select the *Percentages* option, which makes possible an exhaustive inspection of the whole image to determine the total amount of the mineral in the image (as a percentage).

It should be pointed out that to determine the copper grade, according to the experts it is enough to consider the presence of six minerals that contain the copper: chalcopyrite, chalcosine, covelline, bornite, pyrite and energite. For that reason the NN was trained to recognize the patterns of those six minerals.

Under constant data capture conditions it can be stated that one of the 6 minerals studied in a digitized sample has similar texture in different samples. Based on this, the NN's input is a **histogram** of the ROI of the digitized image that corresponds to the counting of the number of pixels classified according to its color level. The NN's architecture must be capable of learning these textures by classifying their characteristic histograms. After analyzing the characteristics of the 6 minerals that contain copper, it was considered possible to compress the histogram to 23 intensities, which are sufficient to distinguish the minerals.

The learning process took place through a backpropagation NN, based on the histogram of a ROI of 15x15 pixels of the image, and identifying that ROI with a given mineral. After determining the number of neurons in the hidden layer using the process indicated in [6], the NN had the following characteristics:

- 23 input units corresponding to the intensities of the histogram;
- a 13-unit hidden layer; and
- a 7-unit output layer, one to identify each mineral and another one for an unrecognized mineral.

The state of an output neuron *j* in layer *s* is given by Eq. 1. The input histogram is mapped in the [0,1] interval, which corresponds to the highest sensitivity region of the transfer function *f(z)*.

$$x_j^{[s]} = f\left(\sum_i \left(w_{ji}^{[s]} x_i^{[s-1]}\right)\right), \quad \text{where } f(z) = \left(1+e^{-z}\right)^{-1} \tag{1}$$

$w_{ji}^{[s]}$ is the connection weight from neuron *i* in layer *s*-1 to neuron *j* in layer *s*. The weights are fitted iteratively as shown in Eq. 2.

$$\Delta w_{ji}^{[s]} = \varepsilon^{[s]} \varepsilon_j^{[s]} x_i^{[s-1]} + \alpha^{[s]} \Delta w_{ji}^{[s]}(t-1) \tag{2}$$

$\varepsilon_j^{[s]}$ measure of local error in neuron *j* of layer *s*, $\varepsilon^{[s]}$ learning coefficient of layer *s* and $\alpha^{[s]}$ momentum coefficient.

To determine the number of neurons in the hidden layer, successive trainings were carried out gradually increasing the number of neurons in the hidden layer, according to the process indicated in [6]. The best results after this fit were obtained with 13 neurons in the hidden layer, with the following parameters: $\varepsilon^{[1]} = 0.4$; $\varepsilon^{[2]} = 0.4$; $\alpha^{[1]} = 0.8$; $\alpha^{[2]} = 0.8$; number of training cycles: 60,000; and the learning coefficient was decreased 10% every 10,000 cycles.

3. Mineral Recognition Process per Rectangle

In the recognition process a method of selecting the ROI was implemented in which the expert selects a rectangle of variable size of the image using the mouse, and then applies the procedure detailed below.

a. The histogram of the selected ROI is generated with 256 values.
b. The 256 values are transformed into an interval of 22 (interval 23 is set at 0), to generate the input to the NN.
c. The size of the selected ROI is normalized at the standard size through which the NN learned (15x15 pixels). This normalization is linear, leaving the result in a vector with 23 values which is passing by for the NN.
d. Every value of this vector is normalized again because it must be in the [0,1] range to be able to go into the backpropagation NN.
e. Finally, the input vector to the NN is available and it is processed by means of the propagation algorithm, getting the result in the output vector.
f. Six of the 7 output units represent a mineral. If there is an excited neuron above the value 0.6 (determined by the expert), then it is highly probable that the selected ROI is that mineral. If no neuron reaches the threshold, the sample is not sufficiently clear, and the background neuron is excited (Table 1).

Table 1. Minerals for determining the copper grade

Output	Mineral
oi[0]	Chalcopyrite
oi[1]	Chalcosine
oi[2]	Covelline
oi[3]	Bornite
oi[4]	Pyrite
oi[5]	Energite
oi[6]	Background

The recognition process by percentage carries out an exhaustive coverage of the image, scanning it totally through two cycles in which it considers the size of the ROI selected by the expert (for this case it was *5*). The result is found as the amount of i^{th} mineral was recognized.

4. Results

The NN implemented was trained with 160 digitized photographs of samples obtained directly from the prospected land. Those 160 photographs analyzed by the expert allowed the NN to be trained. To evaluate the recognition of the different types of minerals in the samples, a test was made with 240 photographs that were not used in the training of the NN. The results showed that 97% of the images used to train the NN were recognized correctly in the percentage mode. Of the new images submitted to the NN, it was capable of recognizing correctly 91% of the samples.

The problems of poor classification can be attributed to the fact that some ROI of the images show superposition of two or more minerals, making the histograms unclear. This problem can be solved using a smaller window.

Every mineral sample in which the expert must determine the percentage of the minerals takes about 15 minutes per briquette. The photographs of the 400 briquettes mean 100 hours of work, and considering 8 hours per workday, they require 12.5 days from the expert. The automatic recognition of the 400 photographs takes less than 20 minutes, which is a substantial improvement in the time used for this process of recognition.

5. Conclusions

In the experts' opinion, the results obtained indicate that the type of neural network described here allows a satisfactory automation of the process of mineral recognition for the problem of prospecting for copper ores.

In the mineral recognition mode the system is simple to use. It is only required to select the ROI that it is desired to recognize, and the system indicates the degree of certainty of the recognized mineral.

In the percentage mode, the automatic system described showed to be reliable in a high percentage of correct recognition (93%) and fast when compared with the time taken by an expert for that work.

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