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A backpropagation ANN algorithm based on RGB images for the identification of granite-forming minerals

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***Abstract* – Granite is a rock widely used in the built Cultural Heritage in the NW of Iberian Peninsula. Nowadays, one of the most studied cleaning procedure of the built Cultural Heritage is the laser application because it is gradual and selective. Considering the laser cleaning of granite, it is of great interest to perform the identification of the forming-minerals in the stone surface in order to avoid damage due to the overexposure, improving the treatment results.**

The aim of this work is the optimization of a back propagation artificial neural network in order to obtain rapid and reliable identification of forming-minerals in granitic stones by means of RGB images. Our goal is, eventually, *in-situ* monitor the laser cleaning of granite stoneworks. The artificial neural network results obtained were compared with the results of the modal analysis and it was detected a high degree of correct identification of the minerals.

I. INTRODUCTION

Laser application is a well-stablished technique used as a cleaning procedure of stones in façades and monuments in the Cultural Heritage (CH) [1, 2]. Different works have been developed using different laser sources, wavelength, stones and surface coatings, mainly in carbonate stones, such as marble and limestones [1, 3]. Among the laser sources investigated; nanosecond- (mainly Nd:YAG or Nd:YVO_4), ultrashort- and femtosecond-pulse lasers [4-7].

Granite as the main stone building in the NW of Iberian Peninsula has been investigated in the recent years [8, 9], being these researches centred mainly on the evaluation of the application of different laser sources to clean different types of coatings that affect severely to the CH objects: graffiti, black crust and biological colonization [2 and references therein]. Through all those works, it was observed that the polymineralic composition of this stone with mineral grains with different chemical and physical properties, is the reason of the different behaviours exhibited by each forming mineral after the laser beam action. For instance, biotite melting is a remarkably damage that it was found in the surfaces irradiated with Nd:YVO_4 laser even at low fluence [9]. In addition to biotite fusion, K-feldspar fusion was also detected in an approach to the black crust cleaning with Nd:YAG laser [10]. Also, a pinkish granitic surface experimented some colour changes due to the hue fading of the K-feldspar grains when they were subjected to Nd:YAG laser [11]. Thus, it becomes very important to perform the adjustments of the irradiation parameters to ensure a satisfactory cleaning without any damage of the different forming- mineral of the substrate.

Considering all above, the automatic control of the laser cleaning requires the rapid and reliable identification of the granite forming-minerals in the surface to be irradiated in order to avoid the damages

reported before.

Backpropagation artificial neural network (ANN) algorithms are used widely as solutions to classification and prediction problems in different fields, among them CH studies [12-15].

The main objective of this paper is the identification of granite forming minerals by means of RGB images processed through a backpropagation ANN algorithm in order to attain, eventually, the automatic adjustment of laser irradiation parameters in the laser cleaning avoiding the damage of the granite forming-minerals due to the laser overexposure.

II. GRANITE SAMPLES

This study was performed over samples of commercial granite from the NW Iberian Peninsula named Rosavel, Rosa Delta and Marrón Estrela. All of them present porphiric texture due to the large size of k-feldspar and plagioclase grains surrounded by an irregular mosaic. Rosavel is pinkish granite with alkali feldspar phenocrystals up to 60 mm length composed of K-feldspar (43 %), quartz (25%), plagioclase (22%), biotite (9%) and accessory minerals (1%). Rosa Delta is a pinkish monzogranite with larger crystals of feldspar and, in a lesser extent plagioclase, reaching up to 5 cm size. It is composed of K-feldspar (45%), quartz (21%), biotite (15%), plagioclase (10%) as main minerals and accessory minerals (9%). Marrón Estrela is a clear-brownish, coarse grained granite, with larger feldspars grains of 2-5 cm size. It is composed of K-feldspar (30 %), quartz (26%), plagioclase (29%), biotite (5%) and accessory minerals (10%) [16].

Samples used in this study were honed slabs of 2 cm thick and 7×15 cm^2 area.

III. ANN DESIGN AND PERFORMANCE

The ANN used in this work was a conventional feedforward perceptron with a three-layered structure. The weights were optimized through the back-propagation learning algorithm. Owing that the aim of this study was the classification of the major granite forming-minerals; i.e. quartz, feldspars, plagioclase and biotite, four neurons in the output layer were considered with output values between 0 and 1. Regarding the input layer it consisted in three neurons to enter RGB values of each pixel in the image (3 integer values of 8 bits, i. e., between 0 and 255). Furthermore, in this work, different number of hidden neurons was essayed to optimize mineral identification (Fig. 1). The complete process was performed using MatLab Neural Network Toolbox [17].

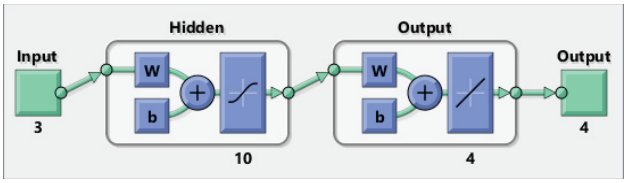

Fig. 1. Schematic diagram of the ANN.

By means of a conventional digital camera, images of the granite slabs were obtained. In these images different regions (sub–images) were selected which correspond to crystal grains of quartz, k-feldspar, plagioclase and biotite. A total of five sub-images were selected for each forming mineral, as it can be appreciated in Fig. 2, which correspond to Rosa Delta granite. Mineral crystals had been previously identified with the help of a microscope.

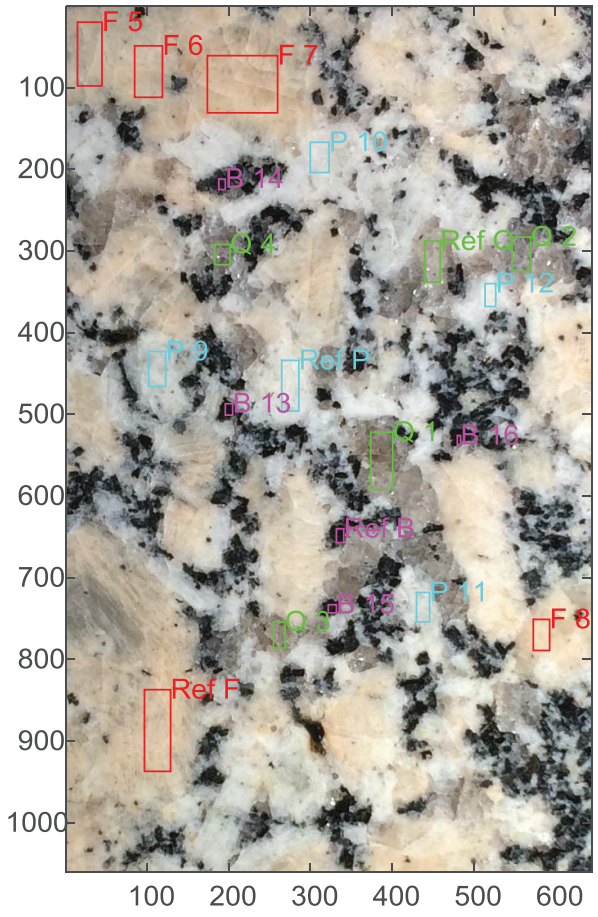

Fig. 2. Image of Rosa Delta granite showing the sub-images which correspond to different mineral crystals. Q: quartz, B: biotite, P: plagioclase, F: K-feldspar

A ANN training

The number of pixels of each mineral class used for training the network are shown in Table 1 and the histograms of the RGB target data of quartz, K-feldspar, plagioclase and biotite crystals, respectively, can be seen in Fig. 3. The target outputs used in the training process were quartz (1, 0, 0, 0), K-feldspar (0, 1, 0, 0), plagioclase (0, 0, 1, 0) and biotite (0, 0, 0, 1).
To evaluate the network performance during training, the 70% of input data was used as training set; 15% as validation set and the remaining 15% was reserved for testing the network. The purpose of validation stage was to determine the stop training to avoid overtraining, i.e., the network loses its ability to generalize. So, the mean square error (MSE) was calculated and the overtraining detected as an increase in MSE of the validation set (see Fig. 4).

Table 1. Number of pixels used to train the networks.

Mineral	Rosavel	Rosa Delta	Marrón Estrela
Quartz	5612	4035	7398
Feldspar	24655	11685	2465
Plagioclase	4081	2915	2838
Biotite	475	457	468

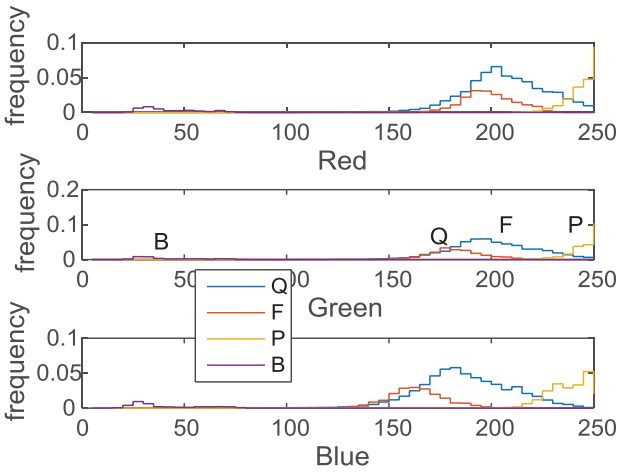

Fig. 3. RGB values of the pixels used to train the network of quatz (Q), K-feldspar (F), plagioclase (P) and biotite (B) minerals.

Furthermore, in this work, test set was used to evaluate the performance of the network as a function of the number of hidden neurons. It can be appreciated (Fig. 5) that depending on the granite, above 5 neurons in hidden layer, a slight improvement in network performance is attained. So the ANN used in this work has 10 neurons in hidden layer.

B ANN Results

The results obtained; i.e.; ANN output for quartz, K - feldspar, plagioclase and biotite in Rosavel, Rosa Delta and Marrón Estrela granites, are shown in Table 2. As it can be observed, a high percentage of correct assignment was obtained, though some misassignments occur, such as the case of quartz in Rosa Delta, or quartz and K-feldspar in Marron Estrela. Furthermore, minerals allocation in Rosa Delta granite is depicted in Fig.6; the correspondence between mineral crystals in granite slab (Fig. 1) and ANN output can be seen.

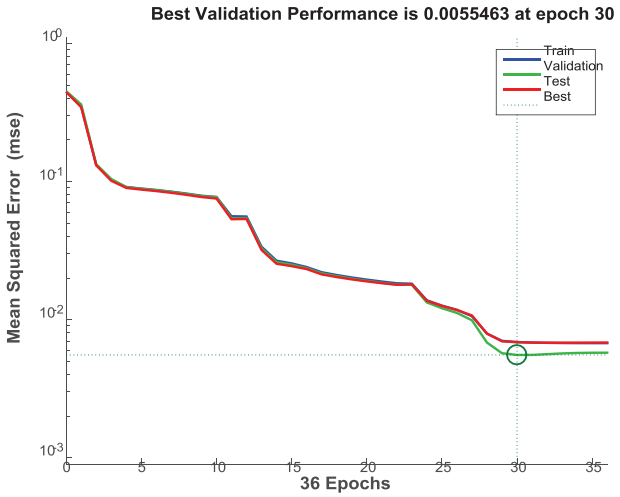

Fig. 4. Mean squared error (MSE) evolution as a function of the number of training epoch. An increase of MSE for the validation dataset indicates overtraining.

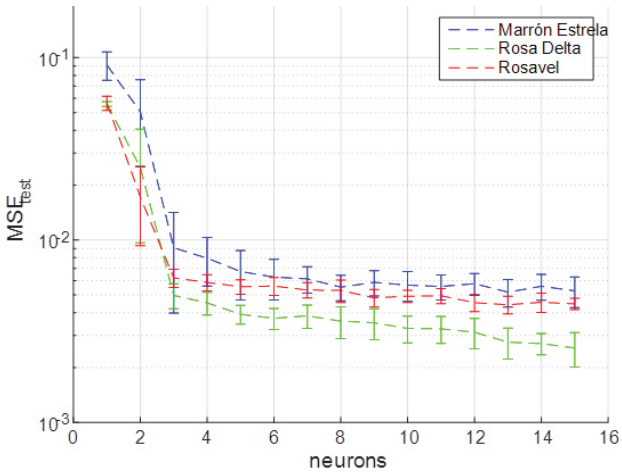

Fig. 5. MSE of test data as a function of neurons in the hidden layer.

On the other side, the ratio (% area) of each mineral in the granite samples, estimated through the neural network results was compared to the modal analysis. The results were in good agreement, especially in the case of Rosavel and Delta Lugo, although, it should be noticed that modal analysis data correspond to % volume, while those obtained through RGB-ANN are % area.

Table 2. Minerals assignation (ANN output) corresponding to the test data input.

Rosavel				
Mineral	% Q	% F	% P	% B
Quartz	96.5	3.4	0.1	0.0
Feldspar	0.2	99.7	0.2	0.0
Plagioclase	0.1	1.3	98.6	0.0
Biotite	0.0	0.0	0.0	100.0
Rosa Delta				
Mineral	% Q	% F	% P	% B
Quartz	47.8	28.0	24.1	0.0
Feldspar	0.0	100.0	0.0	0.0
Plagioclase	2.0	5.2	92.8	0.0
Biotite	0.0	0.0	0.0	100.0
Marrón Estrela				
Mineral	% Q	% F	% P	% B
Quartz	95.8	1.3	3.0	0.0
Feldspar	29.6	70.4	0.1	0.0
Plagioclase	0.0	0.0	100.0	0.0
Biotite	0.0	0.0	0.0	100.0

Table 3. Estimated ratio (% area), obtained from the ANN output, of each of the forming-minerals in the granites.

Mineral	Rosa Delta (% area)	Rosavel (% area)	Marrón Estrela (% area)
Quartz	31.9	24.5	38.5
Feldspar	38.0	46.8	17.5
Plagioclase	18.3	22.3	35.5
Biotite	11.8	6.5	8.6

IV. CONCLUSIONS

In this work, they have been presented preliminary results which indicate the suitability of artificial neural networks for identifying crystal minerals of quartz, K-feldspar, plagioclase and biotite in granite by means of RGB data of the digital images. The performance of a conventional backpropagation three layered perceptron, with three neurons in the input layer and four neurons in the output layer was analysed as a function of the number of epochs of training to improve the ability of minerals identification and avoid overtraining. Furthermore, the number and hidden neurons was also studied. The results of ANN with ten hidden neurons were presented and demonstrated high percentage of correct allocation of the major forming-minerals in Rosavel, Rosa Delta and Marrón Estrela granites.

These results were used to estimate the proportion (% area) of each mineral in the different samples of each granite; getting close to those provided by modal analysis, although with discrepancies which may be due to the latter is calculated as % vol.

Owing that our long-term goal is the automatic identification of granite foming-minerals to develop automatic control of laser cleaning processes, further work is required to improve performance of this method, and its application to mineral identification in other granites.

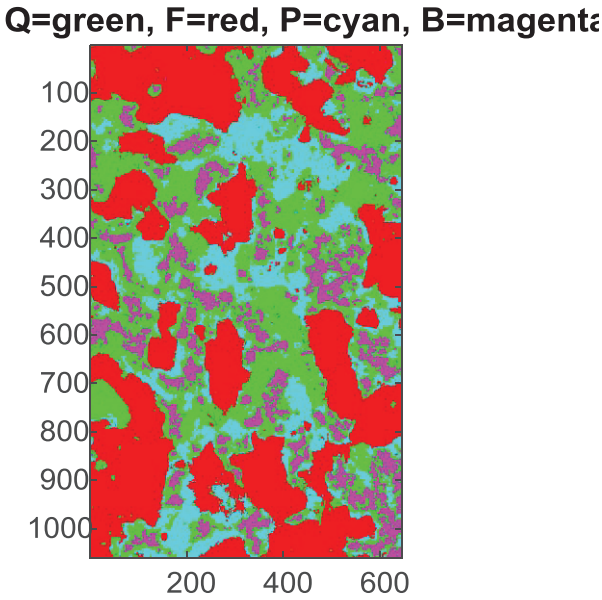

Fig. 6 Estimated allocation of minerals in Rosa Delta granite from ANN output. Q: quartz, F: K-feldspar, P: plagioclase, B: biotite.

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