HYPERSPECTRAL DATA PROCESSING USING NEURAL NETWORKS: PRELIMINARY RESULTS FOR MAFIC MINERALS IN SNC'S METEORITES. A. Rozel[1], H. Clenet[2,3], S. Douté[4] and C. Quantin[2], [1]Dipartimento di Scienze Geologiche, Universita degli Studi "Roma TRE", Italy, [2]Laboratoire de Géologie de Lyon, UMR CNRS 5276, Université Claude Bernard/Ecole Normale Supérieure de Lyon, France, [3]Earth and Planetary Science Laboratory, Ecole Polytechnique Fédérale de Lausanne, Switzerland, [4]Institut de Planéologie et d'Astrophysique de Grenoble, UMR CNRS 5274, Université Jospeh Fourier, France (antoinerozel@gmail.com, harold.clenet@epfl.ch).

Introduction: Mafic minerals are key components when trying to understand the geological history of planetary bodies like Mars. Indeed, their presence in igneous rocks is directly related to mantle properties and crystallization conditions. They also partially control the nature of the alteration products which could be formed later on. In this respect detection of olivine and pyroxenes, and characterization of their respective composition, is an important step that must be done carefully.

Because of the Fe^{2+} electronic transition effect, hyperspectral remote sensing in visible/near-infrared is a very powerful tool to achieve this objective. Indeed, olivine and pyroxenes have characteristics absorption features in the 1 and 2 μm domains [1,2]. During the last decade, imaging spectrometers onboard spacecraft have acquired huge amount of such data and it is actually challenging to process them both quickly and efficiently.

Several techniques aim at deconvolving absorption bands in terms of mineralogy (e.g. linear unmixing, radiative transfer modeling). Modified Gaussian Model can also be used to quantitatively estimate the chemical composition of each mineral in a rock. Such approach has been successfully applied on OMEGA data [3]. However, the results obtained with those techniques are basically not accurate enough, these methods are time consuming and efforts are still done to develop new algorithms. This is why we test in this study the ability of neural networks to detect and characterize mafic signatures on unknown laboratory spectra.

Neural network implementation: A neural network is a mathematical operator which takes a vector of scalars as input and outputs another vector of scalars. In our case, the input vector is the spectrum and the output vector is the mineralogic composition (percentage of olivine, clinopyroxene and orthopyroxene, cf. figure 1). Neural networks are made of weighted and non-linear connexions from the input to the output, typically performing a small number of operations. This technique is sometimes used to obtain a result in very non-linear problems.

Before using a neural network on unknown problems, it has to be trained on known problems in a "learning phase". The network first "learns" to reproduce a sufficiently correct output vectors using a set of spectra obtained on synthetic samples with known compositions (the training set). The connexions of the network start from a random state and are organized by the learning algorithm following a uniform gradient descent in the error space. At the end of the learning phase, the neural network is able to give a correct answer on all the training set. The training is usually the computationally time-consuming phase (about 10 minutes on a single CPU machine in our case).

Second, once trained, the neural network can be used on an unknown spectrum and output a composition. The answer of a neural network is almost instantaneous (less than a second on the same machine, mainly due to input/output on the hard drive).

We use the multilayer perceptron feedforward approach, with an error extended back-propagation learning algorithm [4]. To ensure an homogeneous coverage of the output space, we assigned more weight to the most singular spectra in the back-propagation routine.

Training and testing data sets: Our neural network has been trained on a set of 190 spectra, some of them being representative of mixtures while others are representative of mono-mineral samples with various chemical compositions (mafic minerals only). Because of the lack of available laboratory measurements, very few ternary mixtures are included in the learning set.

All the spectra come from the Brown/RELAB library. Most of them have already been used in [5] to improve MGM approach and a reference list of RELAB files can be found there. We select the wavelength range between 0.46 and 2.60 μm while keeping full spectral resolution (6.6 nm). We remove the first order approximation of each spectrum to give an input signal as flat as possible to the neural network.

To test our neural network, we choose to use spectra of SNCs as those meteorites may be the most representative samples of Mars surface measurable in laboratory. SNCs have been intensively studied and their mineralogical compositions are well known (e.g. [6] and references therein). We here used a set of 11 spectra, representative of the different families of SNCs. One should note that for ALH77005 and EET79001, 3 spectra are analyzed while not knowing exactly which phase of the meteorite is actually measured.

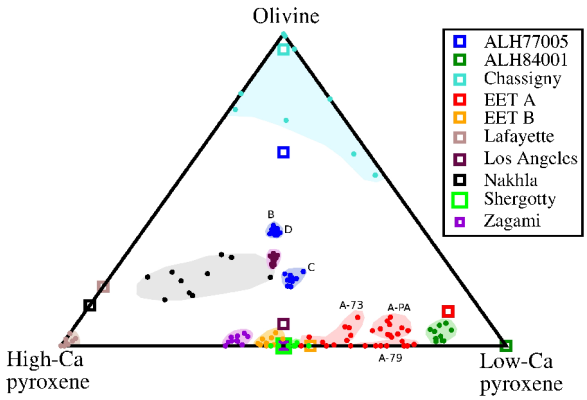

Fig. 1: SNCs modal compositions estimated using neural networks (dots) compared to literature (squares, from [6]). Neural network is tested with different initial neural weights so several dots are reported for each SNCs (see text for details). When different spectra exist for one SNC, results are distinguished using labels around the colored fields.

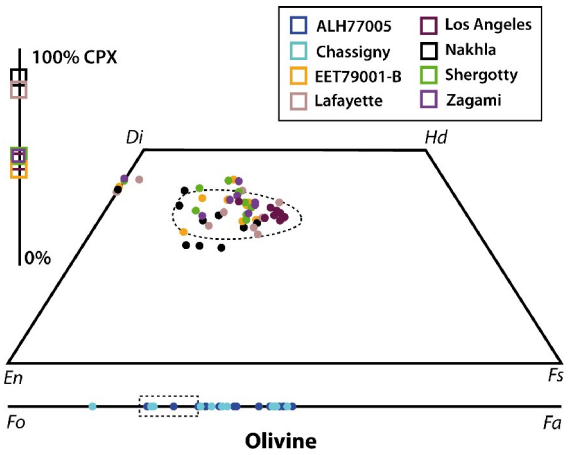

Fig. 2: Chemical compositions of two individual mafic minerals in SNCs estimated using neural networks (dots) and compared to literature (dashed lines, from [6]). The composition of clinopyroxenes is depicted on the top triangle and olivine composition is shown on the bottom line. Clinopyroxene modal abundances in the meteorites are also reported.

Results on SNCs: Figures 1 and 2 show the results of the neural network on the testing set (spectra of the SNCs' meteorites). To explore the reproductibility of the solution, we trained 10 identical neural networks with different initial neural weights. All networks used here have only one hidden layer with 40 neurons. The figures show that the outputs of the networks (represented by colored points) are focused in different localized areas for each spectrum.

The figure 1 shows the outputs of the network as the OL-CPX-OPX compositions of the tested spectra compared to the average range expected for each meteorite (from [6]). The network is clearly able to detect pure and mixed compositions with a satisfactory reproductibility. Discrepencies can nevertheless occur, especially when a mineral is much less abundant than the other. This may be directly related to the absorption features which could be masked in a mixture spectra and implies as other deconvolution techniques to take detection thresholds into account.

Figure 2 shows the chemical composition of clinopyroxenes and olivines detected in each meteorite, using an other version of the neural network, trained for chemical composition only. Work is still ongoing considering the orthopyroxene component. Though the tested samples have similar CPX compositions, the neural network is still able to distinguish tendencies within the spectra. Localized compositional areas are clearly identified and all of them fall within the expected trends from laboratory measurements [6]. However, iron content in olivine is almost always overestimated (10 to 20%).

The composition of meteorites with very low clinopyroxene contents are very scattered and thus not depicted in the top part of the figure 2 (similarly, we plot only high olivine content outputs in the bottom line). The scattering of the outputs of the network actually seems to be a good indicator of mineralogic enrichment and provides a way to quantify the uncertainty of the output of the neural network.

Conclusion: The neural network we developed in this study show promising results on SNCs. Indeed, only using laboratory data as a training set (i.e. partial coverage of the whole range of possibility), we are able to detect and characterize each mineral phase in an unknown spectrum.

In a next step, we will implement our neural network on an automated procedure which will analyze individually each pixel of a CRISM image. This implies to deal with some additional difficulties (noise, weak absorption features, complex photometry). Then, we should be able to process very quickly and efficiently large amounts of data required to do Martian global "high resolution" geology.

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